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Modelling and Forecasting Volatility in the Fishing Industry: A Case Study of Western Cape Fisheries

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By

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Declaration

I, Jotham Nzombe**,** do hereby declare that this dissertation is the result of my investigation and research, and that it has not been submitted in part or in full for any other degree or qualification to any other University or academic institution.

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J. Nzombe **Date**

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Abstract

The Western Cape Fishing industry has been a subject of discussion in numerous papers, in which the thrust has been to seek ways of sustaining the significantly fluctuating business. Common risk factors have been identified and strategies for managing the fishing business in turbulent periods have been proposed over the years. A closer examination of previous literature as well as empirical evidence indicate that the business has less to do to control or minimize the impact of most of its external factors, which include the Government imposed Total Allowable Catch (TAC) limit, the variability in natural marine populations, environmental factors and fuel price oscillations. In the interest of curbing the variability component which is borne by the internal factors, this study brings on board a quantitative dimension to the evaluation of the four commonly cited internal factors, namely; Earnings Per Share (EPS), Margin of Safety (MOS), Free Cash-Flow (FCF) and the Net-Worth (NW) on volatility of the fishing business. The performance of five large JSE-listed fishing firms: Brimstone, Oceana, Premier Fishing, Sea Harvest and Irvin & Johnson, is investigated with the view of modelling and forecasting their volatilities. Initially, the comparison of volatility forecasts from symmetric and asymmetric GARCH-family models is employed. The results of competing models are tested using cross-validation of mean error measures and the Superior Predictive Ability (SPA) and Model Confidence Set (MCS) tests. Later, a Vector Autoregressive (VAR) model is applied to assess the impact of the four commonly cited internal factors on volatility. The research analysis results reveal a generally high volatility of the Western Cape fishing sector stocks. When univariate GARCH models are applied, the asymmetric GARCH-family models (EGARCH and GJR), with fat tails, appear dominant in the sets of competing models for all stocks, which highlights evidence of the leverage effect in the sector. However, GARCH (1,1), outperformed its counterparts in modelling and forecasting Irvin & Johnson (AVI) and Oceana (OCE) stocks. In the VAR modelling process, the Granger-causality tests indicate limited causal-relationship between EPS, MOS, FCF and the company Net-worth with the companies' volatility measures. The variance decomposition of the 10-year ahead forecast of volatility indicates that volatility lag, free cash flow and net-worth have the largest contribution on volatility in the long-run, followed by margin of safety. In view of the above observations, the research discusses recommendations to the Western Cape fishing business to improve business returns and sustainability.

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List of acronyms

ACF:	Auto-Correlation Function
ADF:	Augmented Dickey-Fuller
AIC:	Akaike Information Criterion
APARCH:	Asymmetric Power ARCH
ARCH:	Autoregressive Conditional Heteroskedasticity
DM:	Diebold Mariano
EGARCH:	Exponential GARCH
EPS:	Earnings Per Share
FCF:	Free Cash-Flow
GARCH:	Generalized Autoregressive Conditional Heteroskedasticity
GARCH-M:	GARCH-in-Mean
GJR:	Glosten, Jagannathan and Runkle
ITQ:	Individual Transferrable Quota
LFC:	Least Favourable Configuration
MAE:	Mean Absolute Error
MCS:	Model Confidence Set
MedSE:	Median Squared Error
MOS:	Margin of Safety
MSE:	Mean Squared Error
PACF:	Partial Auto-correlation Function
QML:	Quasi-Maximum Likelihood
RC:	Reality Check
RMSE:	Root Mean Squared Error
SIC:	Schwarz Information Criterion
SPA:	Superior Predictive Ability
TAC:	Total Allowable Catch
TAE:	Total Allowable Effort
TIC:	Theil's Inequality Coefficient
VAR:	Vector Autoregressive Models

Chapter 1: Introduction

1.0.Introduction and background

The plankton-rich Benguela current makes South Africa's West Coast one of the world's richest fishing grounds. Currently, nearly 75% of all South Africa's commercial fishing takes place along the Western Cape's coastline, according to Van Rensberg (2012). The Western Cape Province has the largest number of registered large commercial fishing companies with a few of them trading on the Johannesburg Stock Exchange (JSE). The province accounted for 85% of all fish exports from the country in the year 2013 (Wesgro, 2014).

However, according to the Irvin and Johnson (I&J) sustainability research report (I&J, 2012), investment in the fishing industry is just said to be subject to high volatility due to numerous non-systematic risk factors, but there is lack of evidence quantifying the actual volatility within Western Cape or South Africa. Most papers on the Western Cape fishing industry serve to, theoretically, express the extent to which the internal and external factors have contributed to high volatility of the sector. Asche, Dahl and Steen (2015) pinpoint that the Western Cape fisheries stocks exhibited high volatility over the past decade, but believe that the high volatility is partially ascribed to the seasonality factor. The bulk of fishery researches in the Western Cape refer to the periodic changes in the total allowable catch (TAC) restriction, fuel price oscillations, environmental factors, ecological volatility as well as uncertainties regarding the natural variability of wild marine populations as the key factors contributing to the significant jumps and falls in the fisheries earnings and share returns.

Several researches converge to the agreement that volatility modelling tools have not yet been exploited within the South African fisheries sector to improve efficiency of management. Kuikka (2008) and Asche et al. (2015) have indicated that investment in the fishing sector still requires robust modelling, hedging and management strategies that will ensure long-term constant yield for investors. It is against the background of this reflection and the empirical evidence that this study has become imperative.

This study seeks to model and forecast the volatility models for five JSE listed Western Cape fishing companies, namely; Oceana, Irvin and Johnson (I&J), Sea Harvest, Brimstone and Premier Fishing, also known as African Equity Empowerment Investments. The literature, developments in the volatility modelling framework and empirical evidence is critically analysed. A juxtaposition of the contemporary symmetric and asymmetric volatility modelling approaches will also be undertaken in this study.

1.1. Problem statement

According to the preliminary analysis conducted by the researcher on the year-on-year sector daily historical stock prices for the period 30 June 2014 to 31 May 2016 (two-year period) for the companies Oceana and Irvin & Johnson, the JSE listed fisheries stocks exhibit significant jumps and drops. The evidence was consistent with the theoretical evidence from the sector researches. The theory of the fishing industry suggests that the fishing industry stock prices are ultimately getting a 'slap' from the drastic variation in ecological volatility for wild fisheries, catch rates, fuel price, earnings and other factors. In addition, Peterman (2005), Asche et al. (2015) and Kuikka (2008) also pointed out that the fishing sector requires robust modelling of volatility as well as in-depth application of hedging strategies for return optimization because of the nature of the business. It is therefore critical to estimate the fisheries stock volatility and to recommend management strategies that will optimize the returns of the sector.

1.2. Aim of the study

The fundamental aim of this research is to model the volatilities of the stocks of JSE listed Western Cape Fishing firms. The study will compare the results of the symmetric GARCH (1,1) and GARCH-M models to those of the asymmetric EGARCH, APARCH and TGARCH (or GJR) models. The trajectory of the industry's risk-return profile behaviour will be investigated retrospectively for the daily industry data ranging from 15 years ago, until the year 2016, to estimate the volatility measure. Aldin (2012) indicate that company performance, risk factors, attitudes and expectations all affect the stock sentiments hence the stock price, which conform to the postulation in the reviewed literature regarding the South African fisheries sector share behaviour. The study will also analyse the association between the variability in stock returns and four internal performance measures, with interest from the investor's point of view as well as sustainability viewpoint. This will be achieved by considering historical co-movements of the firm's earnings per share (EPS), net-worth (NW), the margin of safety (MOS) and free cash-flow (FCF), with the volatility of stock returns. The Vector Autoregressive (VAR) models for each firm, as a function of the four internal factors (EPS, NW, MOS, FCF), will also be examined for the significance of the factors in the firms' volatilities.

1.3. Research objectives

This study seeks to model the volatility of fisheries stocks and assess the impact on volatility of the fluctuations in the four internal performance measures of the firms. The objectives of the study are as follows:

i. To model the volatility of the Western Cape fishing industry;
ii. To assess the impact of the earnings volatility, changes in net-worth, margin of safety and free cash-flow on the performance of the fisheries on the JSE;
iii. To identify management strategies and hedging solutions/ instruments that will mitigate the industry volatility;
iv. To provide recommendations to company managers on approaches to minimise the sector risk.

1.4. Significance of the study

The findings of this study will serve to address the research gap on the volatility of fishing stocks with main thrust on the volatility estimation. In summary, the results can be utilised by managers of fisheries, investment analysts and portfolio managers, the investors and the academic community. The lack of robust quantitative modelling of volatility within the fishing industry is one of the gaps identified in existing literature. Therefore the research results are primarily intended to benefit the managers of fisheries and the industry practitioners through improvement of sector risk-modelling methods and hedging strategies. Nevertheless, investment analysts and portfolio managers need a holistic risk-return assessment of every potential stock into which they can invest. In that regard, the results are expected to improve analysts' insights regarding the factors that play a part in influencing fishing stock dynamics to aid their future fundamental and technical stock evaluations for asset selection. The current and potential investors, likewise, need to have as complete information as possible about their potential areas of investment.

The research output may also help address the knowledge gap in fishing industry researches. The study results may improve insights on factors influencing fisheries stocks, potential hedging tools for fishery firms which are found to be in circumstances highlighted in this research project, and further share knowledge on uncertainties of the sector businesses. Academic researchers may also benefit on understanding relationships between the volatility of fisheries stocks and the internal performance factors of the firms. Therefore, the study results are expected to provide background insight for further academic researches

Chapter 2: Literature review

2.0. Introduction

In the quest for modelling and forecasting of volatility in the Western Cape fishing industry, the work of pioneers in volatility study is reviewed. Firstly, volatility is defined as it is applied in finance, highlighting the differences between "realized" and "implied" volatility. The general theoretical stylized facts and features of stock prices are explored. The history of the developments in volatility models in finance leading to the current popular methods in application is also surveyed whilst highlighting the benefits and shortcomings of the methods applied in this study. The volatility of the South African fishing industry with specific focus on Western Cape fisheries is also investigated.

2.1. Volatility

Kempthorne (2013) defines volatility as the conditional variance of an asset return. However, in finance, the standard deviation (σ) is the statistic normally applied as the proxy for traditional volatility measurement. It expresses the degree of variation of a trading price series in the given period of time. Bloom (2009) explains the equity market volatility as the canonical measure applied by finance professionals to proxy for uncertainty in the general financial markets.

Meier (2015) explains that generally two categories of volatility exist, namely; realized and implied volatility. The realized volatility, which refers to the current volatility estimate, is estimated from observed time series data. The reduced-form models are the popular approach for estimating the realized volatility and they include the weighted moving averages (WMA) models and the GARCH models. In contrast to the realized, implied volatility is defined in Brownlees, Engle and Kelly (2011) as just a future volatility forecast and not an estimate of current volatility. It refers to the volatility derived from the market price of the market traded derivative of a stock, particularly an option with a horizon given by the maturity of the option. The latent or stochastic volatility models are the common approach for implied volatility estimation. The most popular latent model is the famous Black-Scholes formula.

The reduced form branch of models is of major importance in understanding historical performance of stocks while the latter is commonly applied for the purpose of pricing derivative securities. However, according to Meier (2015) option prices usually overestimate the likelihood of an equity-market move, hence the implied volatility is typically greater than realized volatility. However, the volatility modelling approach implemented is determined by the objective of the analysis. Thus, for pricing purpose, latent models are more appropriate. If the objective is tracking historical performance of companies, the reduced-form models become more appropriate. The thrust of this study is on tracking the performance of stocks over the past 15 year-period. Therefore, realized volatility is the mere subject of this research.

Alexander (2000) mathematically expresses the scenario reflecting an increase in volatility of stock between times t and $t + 1$. If a time series of stock price S becomes more volatile between two given time periods t and $t + 1$ then, in probability terms, $P(|S_{t+1}| > c) > P(|S_t| > c) \ \ \forall c$, where c is some constant. Thus, an increase in volatility of a security implies that the share price ranges of the subsequent time period is wider than that of the previous period, which has a lower volatility.

2.2. Stylized facts about asset price behaviour

Copious finance researches conducted over the years established five major empirical truths (called stylized facts) across a wide range of instruments, markets and time periods, to which theory is expected to fit. According to Engle and Patton (2001) and Alberg, Shalita and Yosef (2008), a good volatility model must be able to capture and reflect these stylized facts.

2.2.1. Volatility exhibits persistence and clustering

Modern finance theory ascribes to the fact that volatility of stock prices tends to exhibit persistence. The persistence leads to volatility clustering, a concept that was uncovered through the work of Mandelbrot (1963) and Fama (1965), cited in Chong, Chun and Ahmad (2002). Clustering implies that a turbulent trading day tends to be followed by another turbulent day while a tranquil period also tends to be followed by another tranquil period. The implication of volatility persistence and clustering is that volatility shocks today will influence the expectation of volatility many periods that follow. Thus, the forecast of future volatility depends on today's information set (denoted Ω), such as today's returns. The persistence phenomenon was also affirmed in Alexander (2000), Poon (2005) and Alberg et al. (2008).

Let the expected value of the variance of returns k periods in the future be given by:

$$h_{t+k|t} = E_t[(r_{t+k} - m_{t+k})^2] \quad \cdots \qquad (1)$$

By taking the partial derivatives, the forward persistence is generally expressed as:

$$\theta_{t+k|t} = \frac{\partial h_{t+k|t}}{\partial r_t^2} \quad \cdots \qquad (2)$$

The value $\theta_{t+k|t}$ is a dimensionless number as squared returns and conditional variance are in the same units.

2.2.2. Volatility is mean-reverting

Engle and Patton (2001) and Satchell and Knight (2007) stated that the volatility of stocks naturally comes in clusters and goes. This implies that a period of high volatility will eventually give way to more normal volatility and vice-versa. Similarly, a period of low volatility will be followed by a rise. This is referred to as mean-reversion. Succinctly, mean-reversion of volatility simply means that there is a normal level of volatility to which volatility will eventually return after shocks. This implies that long run volatility forecasts are expected to converge to their normal level. Studies by Andersen, Bollerslev, Diebold and Labys (2003), Karlsson (2002), Poon (2005) and Brooks (2008) concurred on the mean-reversion tendency of equity stocks. Financial theory suggests that very long forecasts of volatility (long enough) should all converge to this same normal level of volatility, nomatter when those forecasts were made. Satchell and Knight (2007) add that although many practitioners believe the validity of this characteristic of volatility, they often slightly or largely differ on the so-called normal level of volatility, and whether it is constant over time and also in terms of institutional changes.

The mean reversion of volatility implies that the current information set (Ω) has no effect on the long-run volatility forecasts. This feature can be expressed mathematically as:

$$p \lim_{k \to \infty} \theta_{t+k|t} = 0, \qquad \forall\, t \quad \cdots \qquad (3)$$

Equation (3) is commonly re-expressed as:

$$p \lim_{k\to\infty} h_{t+k|t} = \sigma_t^2 < \infty, \qquad \forall\, t \quad \cdots \tag{4}$$

The two expressions are not quite equivalent, but are both commonly used. However, the expression can also be generalized to include processes without a finite variance.

2.2.3. Innovations may have an asymmetric impact on volatility

The asymmetric volatility models impose the assumption that the conditional volatility of the asset is affected asymmetrically by positive and negative innovations unlike their symmetric counterparts. The EGARCH, APARCH and TGARCH (or GJR) are examples of models that capture volatility asymmetry. Advances in time series volatility analysis inform that, in many markets, the impact of negative price moves on future volatility is larger than that of positive price moves. The asymmetry feature is evidenced in the changes in S&P 500 volatility during the financial crisis in 2008, as indicated by Karlsson (2002). The evidence show that, for the end of September and beginning of October of 2008, implied volatility reacted asymmetrically to up and down stock market moves. In some cases, the asymmetry is ascribed to the leverage effect and in other cases to the risk premium effect. The theoretical expression of the initial case is that as the price of a stock falls, its debt-to-equity ratio rises and stocks become more volatile with higher leverage ratios, increasing the volatility of returns to equity holders, while in the latter case, news of increasing volatility reduces the demand for a stock because of risk aversion. According to Reider (2009), the changes in volatility associated with stock market drops are much larger than that which could be explained by leverage alone.

2.2.4. Exogenous variables may influence volatility

In spite of the arguments for and the widespread application of univariate models, some finance researchers do not find comfort in applying these models when there are multiple independent factors as well as cross-correlations in different markets (Engle and Patton, 2001). Modern finance theory indicates that financial assets do not evolve independently of the market around them. Taylor (2004), Alberg et al. (2008) and King, Botha (2014) and Satchell and Knight (2007), indicate that stock movements may show correlation with some exogenous variables, that is, related assets, macroeconomic announcements, scheduled company announcements. Big movements in one asset may be observed to be matched by big movements in another. In some instances, even the deterministic time-of-day effects may also determine the volatility process, according to Engle and Patton (2001). Glosten et al (1993) and Poon (2005) commonly highlight that indicator variables for October and January assist in explaining some of the dynamics of the conditional volatility of equity returns.

2.2.5. Tail probabilities

Engle and Patton (2001) and Poon (2005) agree to the fact that the unconditional distribution of financial time series, for instance, equities, typically exhibit fat tails than those of a Normal distribution due to excess kurtosis. Generally, the standardized fourth moment for a normal distribution is 3, but the typical kurtosis estimates of equities were found to be generally well above 3 (usually between 4 and 50), which is an indication of extreme non-normality of the distribution. Therefore, asset volatility models are expected to incorporate this particular feature in estimating models. Engle and Patton (2001), among others, have also confirmed that the relation between the conditional density of returns and the unconditional density partially reveals the source of the heavy tails. For instance, if the conditional density is Gaussian, then the unconditional density will have excess kurtosis simply due to the mixture of Gaussian densities with different volatilities.

2.3. Classes of volatility models

In general, two broad categories of volatility models exist in the finance market, namely; the reduced-form models and the latent models. The reduced-form models formulate the conditional variance directly as a function of historic data (observables), as specified in Wennstrom (2014) and Islam (2013). Reduced-from models primarily comprises of the Weighted Moving Average (WMA), GARCH and other ARCH volatility models. In general, the latent class formulates models of volatility that are not functions purely of observables, and includes the Black-Scholes model for option pricing. GARCH models are popular in volatility modelling in different market environments. Numerous extensions of the GARCH models have emerged on the market that allow flexibility to suit various circumstances. Bollerslev (2008) identified over 150 different ARCH/GARCH-type models being applied in the financial market, while Hansen and Lunde (2005) compared 330 different

ARCH/GARCH models to test if any type outperformed the GARCH (1,1). Some examples found in the GARCH-type models list are IGARCH, CGARCH, FARCH, STARCH, AARCH, NARCH, MARCH, SWARCH, SNPARCH, TAYLOR-SCHWERT, SQGARCH, CESGARCH, SPARCH, RS-GARCH, STEC-GARCH, FIGARCH, FIEGARCH, GAS, AGAS and AEGAS. However, models which are not applied in this study will not be discussed.

In equity research, univariate GARCH models are more popular. However, in climates where firm-wide risk management is vital, there is a pressing need to model volatilities and correlations in the context of large covariance matrices which cover all the risk factors relevant to the operations of a firm in which multi-factor models have been proposed. Examples of the multivariate GARCH models include the VECH, diagonal VECH and BEKK models. The major limitation confronted in the multi-factor models is that sometimes it is not easy to apply multi-factor GARCH for too large systems due to increasing number of parameters to be estimated (Alberg et al., 2008). Five variations of the univariate GARCH models, GARCH (1,1), GARCH-M (1,1), EGARCH, APARCH and GJR, will be applied in this study and will therefore be the centre of the discussion. The VAR model will merely be applied to get insights about interrelationships of volatility with internal performance measures.

Empirical evidence shows that both the symmetric and asymmetric GARCH models are theoretically appealing and practically widely recommended. The appeal of GARCH models has been revealed in many studies, including recent ones, Alberg et al. (2008), Brownlees, Engle and Kelly (2011) and LaBarr (2014). GARCH (1, 1) is one of the common choices in studies due to its performance and parsimony, exhibited in Engle and Patton (2001), Reider (2009), Alberg et al. (2008) and Ahmed and Suliman (2009). The variations of the GARCH models applied in this study are discussed in this section since the model estimation will be undertaken utilizing the models which borrow from the GARCH category.

2.3.1. GARCH models applied in the study

The GARCH models were developed as a result of the critical review of the deficiencies of all the Weighted Moving Average (WMA) methodologies towards satisfying the volatility persistence stylized fact, which may result in mispricing, as reflected in Alexander (2000) and

Taylor (2004). More customized extensions of the original Vanilla GARCH have been proposed in the academic literature over the years. However, only a few of those models have found good practical applications. Observations on financial time series, including volatility clustering, leptokurtosis and the leverage effect have led to the use of a wide range of varying variance models to estimate and predict volatility.
In this study five variations of univariate GARCH models, which have received considerable attention, are reviewed. The discussion covers the commonly applied two models from the symmetric family; GARCH (1, 1) and GARCH-in-Mean (GARCH-M) as well as the Exponential GARCH (EGARCH), Asymmetric Power ARCH (APARCH) and Threshold GARCH (or GJR GARCH) from the asymmetric family. In the interest of investigating the significance of the internal performance factors in volatility moves, the Vector Autoregressive (VAR) model is also examined.

In general, GARCH models have more than just two parameters to be estimated and as the number of parameters increase the likelihood functions become flat and more complex which makes it difficult to estimate the parameters. For this main reason, the GARCH (1,1) model is preferred to an ARCH model with a long lag, and parameterizations of conditional mean equations are as parsimonious as possible according to Ahmed and Suliman (2009) and Engle and Patton (2001). However, the GARCH (1, 1) has its own shortcomings which include inability to capture asymmetry property.

Various researches indicated that, in general, univariate GARCH models minimise convergence or robustness problems if they are well-specified. It has been further indicated that the univariate GARCH models commonly quickly converge but their main problems may be the lack of proper specification by the user, or inappropriate data. However, the univariate GARCH models have wider applications than their counterparts. Studies involving multi-factor GARCH models often encounter computational problems when attempting to build large positive definite GARCH covariance matrices which are necessary if one is to net the risks from all positions in a large trading book (Ahmed and Suliman, 2009). Burns (2012) also indicated that GARCH models are generally data-hungry, that is, require a lot of data.

To understand the GARCH model formulations, it is necessary to appreciate the origin and theoretical formulation of the Vanilla GARCH model. According to Brooks (2008) and

Wennstrom (2014), the first ARCH model was introduced by Robert Engle in 1982 and later generalised by Bollerslev and Taylor in 1986. A typical GARCH model applies two equations in its formulation; the standard regression model which models the asset return and the second equation which models the conditional variance. It applies an autoregressive time series approach to account for persistence in the volatility. The prime assumptions in the GARCH model are that the volatilities are conditional on each other over time and also that the conditional variance is changing. Empirical evidence show that many financial time series display conditional heteroscedasticity in which volatile periods are interspersed with tranquil periods, that is, clusters of 'bursts' and low volatility characterised by two types of market innovations; good and bad news. At the root of understanding the GARCH models is the distinction between conditional (stochastic) and unconditional (constant) or long-term volatility (Wennstrom, 2014). Wennstrom (2014) explains that in a case where the observed financial data series is assumed to be generated by a stochastic process with time-varying volatility it is not realistic to collapse the data into a single distribution, ignoring the dynamic ordering. Therefore, in such a case, dynamic models will be appropriate in the volatility modelling process. The advantage in GARCH models is that they capture volatility clustering and leptokurtosis (fatter tails than normal). However, the Vanilla GARCH assumes a symmetric distribution which makes it fail to model the leverage effect. In order to address this problem, many variations to the basic GARCH model then emerged in the last two decades (Wennstrom, 2014). Numerous nonlinear extensions of the GARCH model have been proposed; which include the so-called GJR model by Glosten et al. (1993), the Exponential GARCH (EGARCH) model by Nelson (1991) and the Asymmetric Power ARCH (APARCH) model by Ding et al. (1993). Another challenge that may be encountered when using GARCH models is that they do not always fully embrace the thick tails property of high frequency financial time series (Beine, Benassy-Quere and Lecourt, 2002). In order to overcome this limitation, Baillie and Bollerslev (1989), and Beine et al. (2002) applied the Student's t-distribution. Fernandez and Steel (1998) applied the skewed Student's t-distribution in order to model both skewness and kurtosis. Moreover, Harris et al. (2004) utilized the skewed generalized Student's t-distribution to capture the skewness and leverage effects of daily returns to improve the fit of the GARCH and EGARCH models into international equity markets.

The Vector Autoregressive (VAR) model, applied in this study to understand the relationship between several components of a model, was advocated by Sims (1980). This was developed from the realization that shocks in one market may transmit into another market through the phenomenon called ‘volatility spill-over’. VAR models allow the investigation of contemporaneous movements of markets. It prompts the analysis of impulse responses between financial time series, identification of common factors between the different series and application of variance decomposition to establish error components of the series being related.

Next is a discussion of the reviewed literature together with the empirical evidence pertaining to the volatility of the fishing industry in some foreign economies, the South African economy and more specifically, referring to firms in the Western Cape. The nature of the volatilities of the stocks in those markets is discussed as well as the identified contributory factors for both wild-fisheries and aquaculture business.

2.4. Volatility of fishing companies’ stocks in South Africa and other Countries: Evidence

The fishing industry generally reveals a significant information deficiency with regard to analysis of the industry stock performance both in the South African market and many other economies. The information gap has been pointed out to in many papers including Whitmarsh, James, Pickering and Neiland (2000) and Van Sittert, Branch, Hauck, and Sowman (2006).

2.4.1. Evidence on the volatility of global fishing firms

In a qualitative investigation of return variability of the fishing industry in the United Kingdom, Whitmarsh et al. (2000) stated that the available empirical evidence indicated that returns in the fishery sector are highly volatile. In the study, Whitmarsh et al. (2000) attributed the high volatility to fluctuations in catch rates and sector market conditions. The study further articulated that the overall level of industry returns in United Kingdom is crucially dependent on the effectiveness of effort control, which include the Total Allowable Catch (TAC) and the Total Allowable Effort (TAE) restrictions. A research by Ward (2007) in Canberra, Australia, investigated the impact of historical variations in the fishing power and catchability on industry volatility arrived at the same results. Buck (2008), in the US, also analysed the impact of variation in Individual Transferrable Quotas (ITQs) limits on the volatility of fishing industry. An ITQ is an allocated privilege of landing a specified portion of the total annual fish catch in the form of quota shares. Although ITQs are intended to ensure sustainable future fish stocks in the fishing grounds in the long-run, high variation in the ITQ limits (TAC and TAE) contribute largely to the short-term volatility of the fishing sector. ITQs are used in South African fishing sector as well and have been imposed in South Africa in the late 1980s. In the paper by Buck (2008), ecological volatility also contributes to the upsurge of the industry return volatility. The impact of catch limits on volatility has been investigated further in Asche, Dahl and Steen (2015) in the study of Norway fisheries. The study also quantitatively investigated the impact of fish price volatility regimes on aquaculture and wild fisheries stocks along three dimensions which include; technology, species and product type using GARCH models. The results of the research ascertained that the volatility and riskiness is relatively higher for firms mainly backed by wild fishing as compared to their counterparts which focus more on aquaculture due to the fact that aquaculture supported fishing firms have greater control over the variability of their production levels and less uncertainties.

FAO (2012) recently advocated for the growth of aquaculture sector to account for a larger share of total fish supply in order for fishing companies to have a more controlled supply, minimize volatility-magnifying uncertainty and price swings on the fish market. Again, in Norway, Masquera (2013) investigated the variability of the earnings of the four main fishing industry players; Marine Harvest, Leroy, Salmar and Cermaq, and the impact of the volatility on the Oslo Stock Exchange. In the study, Masquera discovered the volatility of three firms, Marine Harvest, Leroy and Salmar, to be significantly high. Masquera (2013) also tested for Granger-causality of return variability on stock volatility in which bi-directional causality was confirmed in three of the four investigated firms. Results indicated that causality flow from fish prices to share prices and also from share prices to fish prices was evident. The volatility was higher in the three relatively larger firms, with Marine Harvest being the most volatile, possibly because the bigger the company, the more stakeholders will be watching the information belonging to the company. Investors will buy or sell shares depending on the available information concerning the company. This will cause the share prices to fluctuate and consequently the company profits. Van Binh and Dumont (2008) investigated the impact of price swings on the fishing industry within Netherlands and detected a high positive association between the two variables with high volatility results. However, Anderson (2007) believes the industry's high volatility is linked to the sector's two-to-three-year production cycle, during which the fish are at the mercy of weather and diseases or simply escape from their pens.

In another case study conducted on South West England fisheries firms in which both qualitative and quantitative approaches were applied by Albernethy, Trebilcock, Kebede, Allison and Dulvy (2010), the study credited a larger part of volatility of the sector in the period between early 2007 and mid-2008 to the volatile fuel prices than the environmental factors and changes in the imposed restrictive management policies. Albernethy et al. (2010) concluded that the fishing industry is threatened by fuel price volatility because it consumes large quantities of fuel. The heavy fuel consumption by the industry was also pointed to, and was central to Tydemars (2004) study of the North Atlantic demersal fisheries. Tydemars (2004) discovered that, for most fisheries, the energy content of the edible protein from the catch is less than 10% of the fuel energy burnt to catch it. Albernethy et al. (2010) further indicated that the acute fuel price shock in 2007- 2008 period led to most fisheries skippers seeking to increase the fuel efficiency by fishing closer to the port, which reduced exploratory fishing in South West England.

Consistent with the bulk of researches in the universe, the results of volatility modelling obtained by Yeo (2004) using ARMA (1,1), GARCH (1,1) and the GJR (1,1) for various stocks for the same time period in the Western Australia indicated very significant volatility of the fishing stock. In the study, Yeo assessed the impact of risk pressures in the financial markets of environmental industries through the application of univariate GARCH models but noted lack of asymmetric effects in the results. In Japan, Lux and Kaizoji (2006) applied the long memory, fractality and regime-switching GARCH models to model and forecast volatility of 1200 stocks in the Tokyo Stock Market including two fishing companies, Hoko Fishing and Nippon Suisan Kaisha. Volatility of the fishing stocks was consistently noted to be significantly high. More studies were carried out in many countries. However, the concentration of researches in many economies was on identifying factors, and describing the impact on stock performance qualitatively. The approach lacked robust modelling procedures and methodologies.

2.4.2. Evidence on the volatility of fishing firms in South Africa and Western Cape

There is an acute shortage of quantitative research on variability of the sector within the South African economy. However, in the analysis of the South African fishery industry returns conducted in the year 2010 for the period 1990 to 2008 by StatsSA (2010), the industry was regarded as a highly volatile. More studies were conducted on this subject but were mainly qualitative in nature which include the work of Van Sittert et al. (2006) and Asche (2015). However, they cite similar risk factors as noted in Norway, England, Netherlands, Australia and United States. Sea Harvest, I&J and Oceana, particularly, have featured in a number of the Western Cape fishing sector studies conducted.

In a SWOT Analysis carried out by DAFF (2012), the analysis stated the existence of volatility-magnifying risk factors within the Western Cape fishing companies. Mahieu (2015) reflects that offshore aquaculture business is less volatile than wild fishing, and that aquaculture improves the resilience of the stocks of fishing companies within South Africa. Hadassin (1986) also conducted a vital research contributing to this work, which investigated the behaviour of share prices of South African listed companies in relation to their earnings (EPS). However, in Hadassin's study, only one Cape Town firm in the fishing sub-category (Marine Products) was included in the sample and the analysis results on the co-movements between earnings and share prices were provided in a summary fashion, and not firm-specific. Therefore, the results did not provide detailed insight. However, the study identified positive association between industry earnings and share prices. This study seeks to bring more insight to this relationship between share prices and earnings, while factoring in the other three identified key factors, namely; MOS, FCF and NW.

2.5. Conclusion

Overall, the fishing business clearly is challenged by several sector-specific risks. The numerous risk factors and sector uncertainties have contributed to the recent emergence of new exotic derivatives for the volatile fisheries sector in the more financially developed economies. For instance, in Norway, the Norway's Fish Pool Exchange, a Bergen-based group recently launched cleared Salmon Futures contracts in April 2007 between producers, importers, processors and retailers in order to hedge the market. The Salmon is one of the most industrialised seafood sectors, as stated by Anderson (2007). This initiative represents the first time that derivatives technology has been applied to fish. The derivative technology has then been proposed on other species of fish such as tuna, mackerel, cod and herring (Anderson, 2007). The next section gives a brief outline of the methodology followed in this study.

Chapter 3: Research methodology and data

3.0. Introduction

The methodology section stipulates the research pre-conditions and analysis procedure that is followed in the study. It concisely explains each of the set of GARCH specifications employed to model the daily stock returns of Western Cape fishing firms. It also outlines the model forecasting performance measurement procedure, the necessary hypothesis conducted as well as the source and nature of the analysis data applied.

3.1. Research methodology

At the outset, it is vital to confirm ARCH effects on the time series before the proposed GARCH models are applied as pinpointed by Engle (1982). Therefore, the historical data series is initially examined and subjected to Engle's test for the ARCH effects, as supported by Brooks (2014) and LaBarr (2014). Plots of the series' first differences, autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) are examined for serial correlation.

Following a test of ARCH effects, the returns and volatilities for each of the six fishing firms in Western Cape are modelled using the selected GARCH models. A series of the daily stock returns (r_t) are computed from the original stock price series as the continuously compounded returns, which are the first difference in logarithm of closing prices of successive days:

$$r_t = ln\left[\frac{P_t}{P_{t-1}}\right] \quad \cdots \qquad (5)$$

where P_t and P_{t-1} represent the closing stock prices of the current day and previous day, respectively.

To estimate the volatility model parameters, the G@RCH 7 package uses the Gaussian quasi-maximum likelihood (QML) model. Although some of the models estimated are not

Gaussian, the QML estimators are said to be consistent in many studies, assuming a correct specification of the conditional mean and the conditional variance. To maximize the quasi likelihood, the G@RCH 7 package uses numerical gradients and the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization algorithm. To capture different distribution properties of the time series data in this study, three distributions are assumed in the analysis process. The conditional volatility is estimated using the three probability distributions that are available in the G@RCH 7 software package: the Gaussian (normal), t-distribution and, skewed t-distribution. The normal distribution was originally used by Engle (1982) in the ARCH model. Bollerslev (1987), consequently proposed a standardized Student's t-distribution. Furthermore, Lambert and Laurent (2001) extended the skewed Student's t-distribution proposed by Fernandez and Steel (1998) to the GARCH framework. The Python software package is applied to conduct the Superior Predictive Ability (SPA) test and to construct Model Confidence Sets (MCS) on the competing optimal models in order to determine the best performing model.

From the surveyed literature, it is apparent that there is no single universally applicable volatility model. Differences in the current and potential circumstances of financial stocks, assumptions about the stock behaviour, co-movements, persistence and co-persistence of financial assets, stock sensitivity to contagion effects and the beliefs and judgements of the modeller about particular stocks under investigation, all lead to particular choices of volatility models from certain model categories. According to Poon (2005), the perceived changes in volatility and correlation can have important consequences.

In a seminal paper written by Engle (1982), Engle proposed the application of Auto-Regressive Conditional Heteroscedasticity (ARCH) processes using lagged disturbances to model time-varying conditional variance. Evidence based on Engle's study indicated that a high ARCH order is important in capturing the dynamic behaviour of conditional variance. The Generalized ARCH (GARCH) model introduced by Bollerslev (1986) satisfies the requirement as it is based on an infinite ARCH specification in which the number of parameters to be estimated reduce from infinity to only two. ARCH and GARCH models are models with the ability to capture volatility clustering and leptokurtosis. However, as explained by Alberg et al. (2008), since their distribution is symmetric, they fail to model the leverage effect, which is a phenomenon resulting from the asymmetry effect of new positive and negative information. This challenge is addressed by the nonlinear extensions of GARCH model, which include the Exponential GARCH (EGARCH) introduced by Nelson (1991), the Threshold GARCH or GJR by Glosten et al. (1993) and the Asymmetric Power ARCH (APARCH) by Ding, Engle and Granger (1993), among other extensions. Another limitation of the GARCH models is that they do not always fully embrace the thick tails property of high frequency financial time series. Baillie and Bollerslev (1989), and Beine et al. (2002) have applied the Student's t-distribution as a solution to this problem. In an attempt to capture both skewness and kurtosis Fernandez and Steel (1998) applied the skewed Student's t-distribution later found extension to the GARCH framework through the work of Lambert and Laurent (2001). Harris, Kucukozmen and Yilmaz. (2004) further applied the skewed generalized Student's t-distribution to capture the skewness and leverage effects of daily returns and be able to improve the fit of the GARCH and EGARCH models into international equity markets. There are numerous researches in which forecasting of conditional variance was done from asymmetric GARCH models including Brailsford and Faff (1996) and Loudon et al. (2000), cited in Brooks (2008). A comparison of normal density with non-normal ones was made by Baillie and Bollerslev (1989), Lambert and Laurent (2001). In this study, volatility models and forecasts of GARCH (1, 1), GARCH-M, EGARCH, TGARCH (GJR) and APARCH models are estimated applying the different density functions; normal distribution, Student's t-distribution and asymmetric Student's t-distribution.

3.1.1. Symmetric GARCH models applied

According to Islam (2013), symmetric models are simply volatility models that are applied on the premise that the positive and the negative shocks of equal size elicit an equal response from the market. As reflected earlier in Chapter 2, the two symmetric models applied in this study are GARCH (1, 1) and GARCH-in-mean (GARCH-M). The specification of each model is highlighted. To summarize, the first model proposed in this study, the GARCH (1,1), is generally a natural starting point for model comparison due to its ubiquity and progenies, according to Engle and Patton (2001) and Alberg et al. (2008). Two of the key features of this process are its mean reversion and its symmetry. Three of the key features of ARCH/GARCH models useful in modelling include the auto-regression (AR), conditionality (C) and heteroskedasticity (H) of variance. Auto-regression means tomorrow's variance is a regressed function of the variance of the previous period. Conditionality of variance implies tomorrow's variance is conditional on the most recent variance. Heteroskedasticity of variance simply means variances are not constant, they fluctuate over time. In general, all GARCH models have two distinct equations in their specification which capture the key features; the first for the conditional mean and the second for the conditional variance. However, the formulation of the different types of GARCH determines the ability to capture and extent to which the stylized facts embedded in the financial time series can be captured. The following explanations outline the ability to address and degree to which the GARCH models applied in this study address those features above and other ones.

3.1.1.1. GARCH (1, 1)

The simplest GARCH specification is the GARCH (1, 1) model which has just one lagged error square and one autoregressive term. The GARCH (1, 1) model is formulated as follows:

$$r_t = \mu + \varepsilon_t \quad \cdots \qquad (6)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad \cdots \qquad (7)$$

where r_t is the return of the asset at time t, μ is the average return; σ_t^2 is the current conditional variance and σ_{t-1}^2 the previous conditional variance; ω is the weighted long-run (average) variance with the condition $\omega > 0$; ε_t are the residual returns, given by $\varepsilon_t = \sigma_t z_t$ for $t \in \mathbb{Z}$; z_t is a sequence of iid standardized random variables (residual returns), such that; $z_t \sim N(0,1)$. The constraints $\alpha_1, \beta_1 \geq 0$ are vital to ensure that σ_t^2 is non-negative.

This GARCH (1, 1) model is similar to an infinite ARCH model, with exponentially declining weights on the past squared errors, according to Alexander (2000). The GARCH forecasts converge to the long-term average given by the constant, ω. The value of this long-term average is sensitive to the length of data period used to estimate the model. If a period of many years is used, during which there were extreme market movements, the estimate of ω will be high, so current volatility term structure will converge to a higher level and vice-versa. The next proposed model is the GARCH-M which is also a symmetric model but it models expected return as a function instead of a constant, in addition to modelling the volatility.

3.1.1.2. GARCH-IN-MEAN (1,1)

According to Ahmed and Suliman (2009), the return of a financial asset depends on its volatility. The GARCH-M Model may be utilised to model volatility on the premise of symmetric innovations. The GARCH-M model adds a heteroscedasticity term into the mean equation. The simple (parsimonious) GARCH-M (1, 1) has the specification:

$$r_t = \mu + \lambda\sigma_t^2 + \varepsilon_t \quad \cdots \tag{8}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad \cdots \tag{9}$$

$$\omega > 0, \qquad \alpha, \beta \geq 0$$

where the residual ε_t is defined by $\varepsilon_t = \sigma_t z_t$ for $t \in \mathbb{Z}$; and σ_t^2 is the conditional variance at time t, and ω , α, β are parameters. The estimated variance is expected to be positive, so the parameters are constrained to be non-negative.

3.1.2. Asymmetric GARCH models applied

The study further applies four asymmetric GARCH models which are intended to capture the tendency for volatilities to increase more when past returns are negative, hence are able to capture the leverage effect, a concept which implies that bad news tend to have a more pronounced effect on volatility than the good news. In view of the inability of symmetric GARCH models to account for the leverage effects a number of asymmetric models have been introduced to address this phenomenon. In this study, EGAECH, TGARCH and APARCH will be applied to capture the asymmetric phenomenon.

3.1.2.1. Exponential GARCH (E-GARCH)

The EGARCH model was introduced by Nelson (1991). The model is able to account for the asymmetry between up and down moves of stock prices. This model the logarithm of the variance and also accommodates asymmetry due to the fact that negative shocks can have a bigger impact on volatility than positive shocks. Panait (2012) highlights that, in some GARCH models, the non-negativity constraints cannot duly restrain the dynamics of conditional variances. In the EGARCH model formulation, Nelson (1991) eliminated the need for constraints by formulating the conditional variance equation in logarithmic terms as follows:

$$\log(\sigma_t^2) = \alpha + g(z_{t-1}) + \beta\sigma_{t-1}^2 \quad \cdots \tag{10}$$

where $z_t = {}^{\varepsilon_t}/_{\sigma_t}$, so z_t is standard normal, and;

$$g(z_t) = \omega z_t + \lambda \left[|z_t| - \sqrt{\frac{2}{\pi}} \right] \quad \cdots \tag{11}$$

The asymmetric response function $g(.)$, provides the leverage effect as illustrated in the general asymmetric GARCH model above. However, some analysts state that the EGARCH model is difficult to implement although it fits the financial data very well.

3.1.2.2. Threshold GARCH (TGARCH) or Glosten, Jagannathan and Runkle (GJR)

Assuming asymmetric response to the innovations, the volatility model may also be parameterized in the form of the Threshold GARCH (or GJR) model. The GJR includes an extra term that kicks in when there is negative shock. This gives a realistic asymmetry to the volatility model. The GJR model was established through the work of Glosten, Jagannathan and Runkle (1993). It also accounts for asymmetry in volatility estimation as it appends a linear asymmetry adjustment and assumes that equity volatilities are inclined to further increase when past returns are negative. The model's conditional variance equation is formulated as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \, (R_{t-i} - \mu)^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{k=1}^{r} \sigma_{t-k} \, \gamma_k \, (R_{t-k} - \mu)^2 \quad \cdots \tag{12}$$

where σ_{t-k} is an indicator variable, taking the value one if the residual at time $t - k$ was negative and zero elsewhere.

3.1.2.3. Asymmetric Power ARCH (APARCH)

The Asymmetric Power ARCH (APARCH) model was introduced by Ding et al. (1993). As explained by Awartani and Corradi (2005), the APARCH model is a more flexible generalization of the GARCH model. It is expressed as follows:

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{p} \alpha_i \, (|u_{t-i}| - \gamma_i u_{t-i})^{\delta} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} \quad \cdots \tag{13}$$

where $-1 < \gamma_i < 1$ and $d > 0$

The APARCH model formulation includes the general asymmetric GARCH, GJR-GARCH, CGARCH, TGARCH, and others as special cases. According to Awartani and Corradi (2005), the flexibility of the APARCH model leads to some interesting results as evidenced by Giot and Laurent (2001), in which the model specification can be modified to suit the problem.

3.1.3. Preliminary hypothesis tests

Prior to estimating the GARCH models, a preliminary investigation of the data is carried out to examine ARCH effects. ARCH effects are tested using Engle's approach. Also, before the estimation of the VAR models as a function of the internal factors, a unit root test is carried out. Further, Granger Causality Test is conducted to investigate the existence and direction of causality effect between volatility and each of the performance proxy measures on two dimensions; from the investor's point of view as well as from the sustainability view point. From the investor's interest, the effect is assessed only on the earnings per share (EPS) and changes in the firm's equity position. The effect on firm sustainability is assessed based on two dimensions; the changes on the firm's margin of safety (MOS), free cash-flow (FCF) and company net-worth (NW). These variables are assessed through investigation of co-movements and drawing up summary statistics. The variable 'MOS' was technically chosen as a proxy measure for 'profitability' of the firms to avoid confidentiality issues.

3.1.4. Determination of optimal lags for EGARCH, APARCH and GJR models

In this study, the optimal GARCH models are determined through the application of two information criteria, namely; Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). The two measures indicate the optimal lags for each type of GARCH model estimated through the iterative process. The criteria are specified as follows:

$$AIC = ln[\hat{\sigma}^2\ ] + \frac{2k}{T} \quad (14)$$

$$SIC = ln[\hat{\sigma}^2] + \frac{k}{T}\ lnT \quad (15)$$

where $k = p + q + 1, T$ is the size of the sample. The information criteria are minimized subject to the condition that $p \leq \bar{p}\ and\ q \leq \bar{q}$.

3.1.5. Forecasting models for the univariate GARCH models

The forecasting ability of GARCH models is comprehensively discussed by Poon and Granger (2003). The forecasting ability of GARCH models can be evaluated by comparing out-of-sample forecast errors. This study evaluates the 30-day-step-ahead forecasts of the competing models using windows of 30, 60, 90, 120 and 360 days for each of the five fishing firms. This is done for both the mean equation and the variance equation. The forecasts obtained are evaluated using five different measures, namely; MSE, MedSE, MAE, RMSE and TIC. The advantage of using many forecasting measures, cross-validation and the model superiority tests resides in the robustness in choosing an optimal predictor model. An h-step volatility forecast is generally given by:

$$\begin{aligned} Var[y_{t+h}|\Omega_{t-1}] &= E[y_{t+h} - E(y_{t+h}|\Omega_{t-1})]^2 \\ &= E[e_{t+h}^2|\Omega_{t-1}] \end{aligned} \tag{16}$$

where Ω_{t-1} is, the information set available at time $t-1$, e_t are the error terms, where $e_t \sim N(0, \sigma_t^2)$.

3.1.6. Forecasting performance evaluation measures and tests of GARCH models

3.1.6.1. Forecasting performance evaluation measures

Alberg et al. (2008), LaBarr (2014) and Brownlees, Engle and Kelly (2011) motivate a comparison of the performance of the models obtained by the symmetric and asymmetric classes of the models to determine the one that performs best based on results. The study will assess the Monday and Friday effects on the series and test for asymmetric volatility. The out-of-sample forecasting accuracy of each of the models applied is assessed using five measures, namely; Mean Absolute Error (MAE), Mean Squared Error (MSE), Median Squared Error (MedSE), Root Mean Squared Error (RMSE) and Theil's Inequality Coefficient (TIC). However, previous studies reflect that, although the MSE and MAE are relatively easier to calculate, they are scale-dependent and often prone to the effect of outliers in the data series unlike the MedSE, RMSE and TIC. The forecasting performance measures are expressed as follows:

Mean Squared Error:

$$\text{MSE} = \frac{1}{h+1}\sum_{t=S}^{S+h}(\hat{\sigma}_t^2 - \sigma_t^2)^2 \quad \cdots \tag{17}$$

Median Squared Error:

$$\text{MedSE} = \text{Inv}(f_{Med}(e_t) \quad \cdots \tag{18}$$

Where $e_t = (\hat{\sigma}_t^2 - \sigma_t^2)^2$ and $t \in [S, S+h]$

Mean Absolute Error:

$$\mathrm{MAE} = \frac{1}{h+1}\sum_{t=S}^{S+h} |\hat{\sigma}_t^2 - \sigma_t^2| \quad \cdots \tag{19}$$

Root Mean Squared Error:

$$\mathrm{RMSE} = \sqrt{\frac{1}{h+1}\sum_{t=S}^{S+h} (\hat{\sigma}_t^2 - \sigma_t^2)^2} \quad \cdots \tag{20}$$

Theil's Inequality Coefficient:

$$TIC = \frac{\sqrt{\frac{1}{h+1}\sum_{t=S}^{S+h}(\hat{y}_t - y)^2}}{\sqrt{\frac{1}{h+1}\sum_{t=S}^{S+h}(\hat{y}_t)^2} - \sqrt{\frac{1}{h+1}\sum_{t=S}^{S+h}(y_t)^2}} \quad \cdots \tag{21}$$

where h is the number of lead steps, S is the size of the sample, $\hat{\sigma}_t^2$ is the forecast variance, σ_t^2 is the actual variance and y_t are the series values and $\hat{y}_t$ are the forecast values at t.

The forecasting ability is reported by ranking the different models with respect to the above-stated five performance measures. Hyndman (2014) argues that if the 'test set' is small, the conclusions drawn from the forecast accuracy measures may not be very reliable. To solve the problem, cross-validation, which uses many different 'training and test sets', is invoked. The results are averaged across all the test sets to adjust for their different sizes. In this study, a cross-validation, advocated by Hyndman (2014) and Alexander (2000) is performed on 30, 60, 90, 120 and 360-day out-of-sample forecasts.

3.1.6.2. Test of superiority of estimated models

The test of superiority of models has been highlighted by Marino (1996), Hansen (2005) and others as key in establishing the best performing models. Two tests of model superiority are invoked to aid decision-making and selection among the group of competing models, namely; the Superior Predictive Ability (SPA) Test of Hansen (2005) and the Model Confidence Set (MCS) proposed by Hansen, Lunde and Nason (2011).

The two tests apply in a more common setting. However, each approach has its applicable assumptions and a distinguished way of selecting the best model. The studentized SPA test is conducted on the group of competing models to investigate whether the benchmark model for each stock under investigation is outperformed by alternative forecasts. The SPA test, proposed by Hansen (2005), arguably compares favourably to the Reality Check for data snooping (RC) that was proposed by White (2000), cited in Hansen (2005), according to a number of research findings and Monte Carlo Simulations. The MCS procedure is based on tests for Equal Predictive Ability (EPA) and it considers multiple competing forecasts simultaneously with the objective of establishing the forecast alternative which might be the best. The MCS procedure indicates the inferior forecasts which must be discarded from the set. It is benchmark-free but instead yields a 'p-value' for each model.

In constructing the setting for the three tests, suppose y_t is the time series of interest, for $t = 1; 2; \cdots ; T$ and let $\hat{y}_{T+h|T}$ be the forecast of $y_{\mathrm{T+h}}$ made at time T. Assume $t = n + 1; n + 2; \cdots ; n + m = T$ is the out-of-sample forecast period then the forecasts are evaluated by the favourite loss function $L(y_t, \hat{y}_{t|t-h})$ for $t = n + 1; n + 2; \cdots ; n + m$. In general, the reflection that the forecast from model 1, given by $\hat{y}^{(1)}_{t|t-h}$, has a better out-of-sample performance than that of model 2, $\hat{y}^{(2)}_{t|t-h}$, is expressed by the inequality:

$$\frac{1}{m}\sum_{t=n+1}^{n+m}\left[(y_t - \hat{y}^{(1)}_{t|t-h})^2 - (y_{\mathrm{t}} - \hat{y}^{(2)}_{t|t-h})^2\right] < 0 \quad \cdots \qquad (22)$$

In order to determine if model 1 is significantly better, an expected loss differential function, applied in the hypothesis is defined as follows:

$$\mu = E(d_t) \quad \cdots \qquad (23)$$

Where $d_t = (y_t - \hat{y}^{(1)}_{t|t-h})^2 - (y_t - \hat{y}^{(2)}_{t|t-h})^2$

Superior Predictive Ability (SPA) test

Suppose we have m models for some variable y_t, and assume $d_{k,t}$ is the performance measure of the k-th model relative to a benchmark model at time t for $t = 1; 2; \cdots; n$. In the studentized SPA test, to determine if there is a model with predictive superiority over the benchmark, one would like to test the null hypothesis that

$$SPA_n = \max\left[\max_{1\le k\le m} \sqrt{n}\bar{d}_k/\hat{\sigma}_k , 0\right] \quad \cdots \tag{24}$$

Where $\hat{\sigma}_k^2$ is a consistent estimator of $\sigma_k^2 = \omega_{kk}$.

The main argument for the normalization, according to Hansen (2005), is that it will improve the power typically. Since it uses a data-dependent choice for μ instead of $\mu = 0$ implied by the least favourable configuration (LFC) condition, it usually leads to a more powerful test of composite hypotheses. The SPA test takes the supremum over a smaller confidence set chosen such that it contains the true parameter with a probability that converges to 1. In the SPA test, the mean $E(d_k) = \mu_k$ is estimated by:

$$\hat{\mu}_k = \bar{d}_k.1\left\{\sqrt{n}\bar{d}_k/\hat{\sigma}_k \le -\sqrt{2loglogn}\right\} \quad \cdots \tag{25}$$

for $k = 1; 2; \cdots; m$ where $1\{.\}$ denotes the indicator function.

Suppose the variable of interest is y_t for $t = 1, 2, \cdots, n$ and also assume that the benchmark forecast is given by $\hat{y}_{B,t}$, with a corresponding loss function of $L_{B,t}$ then we can compare to the forecast by alternative models as illustrated in the Table 3.1 below:

Table 3.1. SPA test: Comparison of loss functions for benchmark and alternatives

Model	Model forecast	Loss function
Benchmark	$B_f = \hat{y}_{B\|t}$	$L_{B\|t} = (y_t, \hat{y}_{B,t})$
Alternative 1 ($k = 1$)	$A_{1f} = \hat{y}_{1\|t}$	$L_{1\|t} = (y_t, \hat{y}_{1,t})$
Alternative 2 ($k = 2$)	$A_{2f} = \hat{y}_{2\|t}$	$L_{2\|t} = (y_t, \hat{y}_{2,t})$
⋮	⋮	⋮
Alternative m ($k = m$)	$A_{mf} = \hat{y}_{m\|t}$	$L_{m\|t} = (y_t, \hat{y}_{m,t})$

Thus, the expectation of the relative performance variables is defined by:

$$\begin{aligned}\mu_k &= E\left(X_{k,t}\right) \quad \cdots \\ &= E\left(L_{1,t} - L_{2,t}\right)\end{aligned} \tag{26}$$

where $X_{k,t} = L_{0,t} - L_{k,t}$ for $k = 1, 2, \cdots, m$ and $t = 1, 2, \cdots, n$

If $\mu_k > 0$, it means the kth forecast is worse than the benchmark, and if $\mu_k < 0$, it means the kth forecast is better than the benchmark. If $L_{0,t}$ and $L_{k,t}$ are two loss functions for forecasts of two models 0 and k, then the SPA tests the Null:

H0: $\mu_k \leq 0$

Model Confidence Set (MCS)

In the objective of forecasting the variable y_t for $t = 1; \cdots ; n$, given a set of competing models $\mathcal{M}_0$, the aim is to construct the procedure that yields the set, $\widehat{\mathcal{M}}^*_{1-\alpha}$, which contains the best model with a probability greater or equal to $1 - \alpha$. If the competing forecasts are $\hat{y}_{i,t}$ for $t = 1; 2; \cdots ; m$ which are evaluated by a loss function $L_{i,t}$ which are ranked in terms of the expected loss $E(L_{i,t})$, then the best model in the set, denoted i^*, is the one that solves:

$E\left(L_{i^*,t}\right) = min\mathrm{n}_i E\left(L_{i,t}\right) \quad \cdots$ (27)

If we consider a set, $\mathcal{M}_0$, with objects indexed by $i = 1; \cdots ; m$. The objects are evaluated over the sample $= 1; \cdots ; n$, in terms of the loss function, $L_{i,t}$. The MCS hypothesis is:

$H_{0,\mathcal{M}}: E\left(d_{ij,t}\right) = 0 \ \forall \, i, j \in \mathcal{M} \subset \mathcal{M}_0$ vs $H_{A,\mathcal{M}}: E\left(d_{ij,t}\right) \neq 0$ for some $i, j \in \mathcal{M}$

where $d_{ij,t} = L_{i,t} - L_{j,t}$ for all $ij \in \mathcal{M}_0$ about which we assume $E(d_{ij,t})$ is finite and does not depend on t $\forall \, i, j \in \mathcal{M}_0$.

The set of superior objects is defined by $\mathcal{M}^* = \{i \in \mathcal{M}_0: E\left(d_{ij,t}\right) \leq 0 \ \forall \, j \in \mathcal{M}_0\}$.

If we define another set $\mathcal{M}^{\dagger} = \{i \in \mathcal{M}_0: E\left(d_{ij,t}\right) > 0$ for some $j \in \mathcal{M}_0$. $H_{0,\mathcal{M}^*}$ is always true given our definition of $\mathcal{M}^*$. $H_{0,\mathcal{M}}$ is always false if $\mathcal{M}$ contains elements from both $\mathcal{M}^*$and $\mathcal{M}^{\dagger}$. Assuming $\delta_{\mathcal{M}}$ is an equivalence test for $H_{0,\mathcal{M}}$ and $e_{\mathcal{M}}$ an elimination rule that identifies the object to be removed from $\mathcal{M}$ if $H_{0,\mathcal{M}}$ is rejected, then the MCS algorithm will be:

Step 0: Initially set $\mathcal{M} = \mathcal{M}_0$

Step 1: Test $H_{0,\mathcal{M}}$ using $\delta_{\mathcal{M}}$ at level α

Step 2: If $H_{0,\mathcal{M}}$ is accepted define $\widehat{\mathcal{M}}^*_{1-\alpha} = \mathcal{M}$, otherwise use $e_{\mathcal{M}}$ to eliminate objects from

$\mathcal{M}$ and repeat steps 1 and 2.

We refer to the set $\widehat{\mathcal{M}}^*_{1-\alpha}$ of surviving objects, that is, those that survive all the tests without being eliminated, as the Model Confidence Test. The individual t-statistics are given by:

$$t_{i.} = \frac{\bar{d}_{i.}}{\sqrt{\widehat{var}(\bar{d}_{i.})}} \quad \cdots \tag{28}$$

$for\ i \in \mathcal{M}$ where $\bar{d}_{i.} = (\bar{L}_i - \bar{L}_.)$

The test statistic:

$$T_{max} = \max_{i \in \mathcal{M}} t_{i.} \quad \cdots \tag{29}$$

where the asymptotic distribution of T_{max} depends on nuisance parameters.

Given the elimination rule satisfies the assumption ** above, then with T_{max} a natural elimination rule is:

$$e_{\mathcal{M}} = arg \max_{i} t_{i.} \quad \cdots \tag{30}$$

The rule removes the model that contributes most to the test statistic, T_{max}, among the models with a sample performance that is worse than the average across models. Specifically, $e_{\mathcal{M}}$ selects the object that has the largest standardized excess loss, relative to the average across all models in $\mathcal{M}$.

3.1.7. Data

The time series data applied the GARCH models is the daily stock prices of five JSE listed fishery firms, namely; I&J Fishing, Oceana, Sea Harvest, Primier Fishing and Brimstone. The stock prices data is collected from the site http://www.finance.yahoo.com/ while the annual FCF, Net-worth, EPS, MOS data was collected via the Bloomberg database. Sea Harvest has relatively few data observations due to delisting which occurred in October 2014, although the firm is planning on relisting this year, 2017. Also, its data only starts from December 2007. Burns (2012) indicated that the best frequency for GARCH is daily since GARCH models are data-hungry. Therefore, the daily data is considered better in this study than weekly, monthly or quarterly data.

3.1.8. Vector autoregressive (VAR) model

The analysis process of this study completes with the estimation of the Vector auto-regressive (VAR) models for each stock. VAR models are econometric models applied to capture the linear interdependencies among multiple time series by allowing for more than one evolving variable in their specification. Lütkepohl (2015) highlights that Vector autoregressive (VAR) processes are popular in economics and other sciences because they are flexible and simple models for multivariate time series data since the models do not need to specify which variables are endogenous or exogenous.

3.1.8.1. Model estimation

The basic form of a VAR process is given by:

$$y_t = Dd_t + A_1 y_{t-1} + \cdots + A_p y_{t-p} + e_t \quad \cdots \qquad (31)$$

where $y_t = [y_{1t}, \cdots, y_{Kt}]'$ is a vector of K observed time series variables, d_t is a vector of deterministic terms such as a parameter matrix, the $A_i{}'s$ are $K \times K$ parameter matrices attached to lagged values of y_t, p is the lag order (or VAR order) and e_t is an error process such that $E(e_t) = 0$ and the covariance matrix $E(e_t e_t{}') = \Sigma_e$, is time-invariant and the $e_t{}'s$ are serially uncorrelated or independent. If the e_t's are independent white noise, the minimum MSE h-step forecast of y_{t+h} at time t is the conditional expectation given y_s, such that, s ≤ t:

$$y_{t+h|t} = E[y_{t+h}|y_t, y_{t-1}, \cdots] = Dd_{t+h} + A_1 y_{t+h-1|t} + \cdots + A_p y_{t+h-p|t} \quad \cdots \qquad (32)$$

Where $y_{t+j|t} = y_{t+j}$ for $j \leq 0$.

Using this formula, the forecasts can be computed recursively for $h = 1, 2, \ldots$. The forecasts are unbiased, that is, the forecast error $y_{t+h} - y_{t+h|t}$ has mean zero and the forecast error covariance is equal to the MSE matrix. The 1-step ahead forecast errors are the e_t's.

3.1.8.2. Preliminary tests: VAR model

Five key tests are performed prior to the VAR model estimation. The tests include; normality, serial correlation, ARCH effects, Group Unit Root, Co-integration and Granger-causality.

3.1.8.3. Post-estimation tests and checks

The estimated VAR model is tested for normality, ARCH effects and serial correlation. In addition, the variance decomposition and impulse responses of the model are also investigated. A Robust Least Squares MM model is also estimated.

3.1.8.4. Data for the VAR model: Annual volatility, EPS, NW, MOS and FCF

The 15-year annual data for the proxies of the firms' internal performance measures, that is EPS, NW, MOS and FCF (independent variables), was downloaded via Bloomberg. The data starts from 01 January 2001 and ends on 31 December 2016. However, SHH data did not exist in the Bloomberg database due to the firm's de-listing which occurred in the year 2014. The firm was consequently excluded from the summary of the results. Therefore, the forecasting results, interpretations and conclusions on results are based on four stocks, that is, BRT, OCE, AEE and AVI. The annualized volatility for each stock is estimated from the estimates of daily volatility.

3.1.9. Conclusion

The final model considered in this study is chosen based on their simplicity, features and ability to forecast and capture commonly held stylized facts. In Chapter 4, a brief description of the volatility model estimation procedures is given as well as presentation of the forecasting results. Also, essential summary statistics and hypothesis are illustrated.

Chapter 4: Empirical Results and Analysis

4.0. Introduction

The analysis of the performance of stocks of fishing firms is performed in a five-step procedure, that is, preliminary test, model estimation, diagnostic check, forecasting performance evaluation and model selection. At the outset, all dependent variables (stock series), BRT, AVI, OCE, AEE and SHH are checked for stationarity. The series are also subjected to preliminary tests which include test for ARCH effects, serial correlation and normality. The proposed symmetric and asymmetric GARCH models are only estimated subject to the fundamental conditions being satisfied for validity. The optimal lags of the models are determined by applying the AIC and SIC criteria. Diagnostic checks for serial correlation, ARCH effects and normality are also performed on the resultant models. A comparison of forecasting performance of the models that pass the misspecification tests is done using five forecasting performance evaluation measures which include the MSE, MedSE, MAE, RMSE and TIC. Further tests and comparison procedures are applied to select the best performing models among the symmetric and asymmetric model groups. The additional tests applied include the Cross-validation, Superior Predictive Ability Test and the Model Confidence Set (MCS). Lastly, forecasts of stock returns and volatility are estimated using the selected best models based on the forecasting performance evaluation tests applied. VAR models of each stock and their forecasts are estimated in order to understand the relationship between volatility and the four internal measures of performance.

4.1. Preliminary tests for GARCH models

4.1.1. Plot of actual series, ACF and PACF

The log return data range for the four firms spans the period from 04 June 2001 to 31 May 2016, except for SHH which only starts from 29 January 2008 to 31 May 2016. The rest of the sample sizes for the return series are more than 3000 observations for each stock except for SHH which has only 558 observations. However, SHH was included in the analysis to just get a picture of volatility behavior of the stock during the time of listing, but the stock's data is not applied for forecasting purpose. The stock was included as its sample size (of the days when the stock was active on JSE) satisfies the minimum sample size of 300 recommended for effective GARCH model estimation in the reviewed literature, including Ng and Lam (2015). Also, no correction was made to its AIC and SIC evaluation measures, as motivated in Hurvich and Tsai (1991), since the sample meets sample-size-to-dimension ratio minimum.

A test of stationarity of the dependent variables, using the Unit Root Test, indicated that all the data series are stationary. Therefore, none of the series required conversion to stationary series. The plot of the actual return series and squared returns exhibits volatility clustering. The clustering of volatility is clearly visible in all the return series, that is, large changes tend to be followed by large changes of either sign, and small changes also tend to be followed by small changes. This is a clear sign of the presence of ARCH effects in all the stock series. An examination of the ACF and the PACF indicate clear strong dependence which show a great deal of persistence in the series.

4.1.2. Hypothesis test of ARCH effects, serial correlation and normality

The following hypotheses were tested on the data series for each of the firms by through the Engle's LM test for ARCH effects, Box-Pierce Q-statistics for serial correlation and the Jarque-Bera for testing normality.

ARCH effects hypothesis:

H_0: There is no ARCH effects

H_A: There is ARCH effects

Serial correlation hypothesis:

H_0: There is no serial correlation

H_A: There is serial correlation

Normality hypothesis:

H_0: Series is normal

H_A: Series is not normal

Using Engle's LM test for ARCH effects, the Null hypothesis (no ARCH effects) is rejected in each of the cases since all p-values are less than 5%. By applying the Box-Pierce Q-statistics on squared data, the Null (no serial correlation) is also rejected which confirms existence of serial correlation. All the p-values of the ARCH LM test and the Box-Pierce Q-Statistics for BRT stock returns are very significant which means the null hypotheses of no ARCH effects and no serial correlation, respectively, are both rejected at 5% level of significance. Therefore, it is concluded that ARCH effects and serial correlation exist in the BRT daily stock return data. Furthermore, from the Kurtosis measures in the statistics for normality test, it can be realized that the kurtosis measure in each case is greater than 3. This reflects the existence of fat tails in the distributions of the BRT series. Also, by applying the Jarque-Bera, the p-value is 0.0000 which is less than 5%, which suggests rejection of the assumption of normality of the series distribution. The same set of tests summarized are also performed on the rest of the stocks which also reveals existence of ARCH effects, serial correlation and heavy tails. The test results support the application of ARCH/ GARCH-type family models to estimate volatility the volatility of the stocks of fishing firms since all necessary conditions are satisfied.

4.2. Estimation of GARCH models

A natural starting point, GARCH (1,1) was first examined for significance of Monday and Friday effects. An examination of the BRT Garch (1, 1) model for Monday and Friday effects indicated no significance of the variables. The rest of the models obtained in the iterative procedures were also tested for the Monday and Friday effects and the two dummy variables indicated no effects in both the mean and the variance equations. The set of the dominating estimated GARCH models and their corresponding AIC and SIC values, in which the optimal models (23 models) are in highlighted columns, are shown in Table 4.1. to Table 4.5. below.

Table 4.1. Brimstone Fishing (BRT) optimal models

Model Type	GARCH	GARCH-M	EGARCH			APARCH			GJR		
Distribution	Stud t	Stud t	Normal	Stud t	Skw Stud t	Normal	Stud t	Skw Stud t	Normal	Stud t	Skw Stud t
Order (p, q)	GARCH (1,1)	GARCH-M (1,1)	EGARCH (8,3)	EGARCH (6,5)	EGARCH (5,4)	APARCH (6,2)	APARCH (3,2)	APARCH (4,3)	GJR (1,4)	GJR (1,5)	GJR (3,2)
AIC	3.602053	3.601127	3.808374	3.574053	3.576677	3.822219	3.572198	3.571299	3.832359	3.583589	3.582817
SIC	3.610320	3.611048	3.833176	3.600508	3.601478	3.843714	3.590385	3.596100	3.850547	3.603430	3.601004

Table 4.2. Irvin & Johnson (AVI) optimal models

Model Type	GARCH	GARCH-M	EGARCH			APARCH			GJR		
Distribution	Normal	Stud t	Normal	Stud t	Skw Stud t	Normal	Stud t	Skw Stud t	Normal	Stud t	Skw Stud t
Order (p, q)	GARCH (1,1)	GARCH-M (1,1)	EGARCH (5,3)	EGARCH (2,3)	EGARCH (3,3)	APARCH (4,1)	APARCH (1,2)	APARCH (1,2)	GJR (3,5)	GJR (3,2)	GJR (1,2)
AIC	4.162940	4.162951	4.144724	3.937077	3.937445	4.144122	3.945604	3.945665	4.141692	3.947973	3.948039
SIC	4.169400	4.171026	4.164104	3.953228	3.956825	4.158658	3.960140	3.961815	4.165917	3.964123	3.962574

Table 4.3. Oceana (OCE) optimal models

Model Type	GARCH	GARCH-M	EGARCH			APARCH			GJR		
Distribution	Normal	Normal	Normal	Stud t	Skw Stud t	Normal	Stud t	Skw Stud t	Normal	Stud t	Skw Stud t
Order (p, q)	GARCH (1,1)	GARCH -M (1,1)	EGARCH (5,5)	EGARCH (1,3)	EGARCH (3,3)	APARCH (3,1)	APARCH (**)	APARCH (**)	GJR (3,4)	GJR (**)	GJR (**)
AIC	3.951292	3.951669	3.933382	3.485428	3.478156	3.949997	**	**	3.934387	**	**
SIC	3.957709	3.959690	3.955841	3.499866	3.497407	3.962831	**	**	3.955243	**	**

Table 4.4: Premier Fishing (AEE) optimal models

Model Type	GARCH	GARCH-M	EGARCH			APARCH			GJR		
Distribution	Skw Stud t	Skw Stud t	Normal	Stud t	Skw Stud t	Normal	Stud t	Skw Stud t	Normal	Stud t	Skw Stud t
Order (p, q)	GARCH (1,1)	GARCH-M (1,1)	EGARCH (2,5)	EGARCH (2,1)	EGARCH (2,1)	APARCH (7,1)	APARCH (1,3)	APARCH (3,3)	GJR (2,3)	GJR (1,3)	GJR (5,2)
AIC	3.039435	3.039961	3.091977	3.043408	3.036793	3.088225	3.042626	3.034636	3.085433	3.042222	3.034229
SIC	3.049356	3.051535	3.110165	3.056636	3.051673	3.108066	3.060813	3.057784	3.101968	3.058757	3.055724

Table 4.5: Sea Harvest (SHH) optimal models

Model Type	GARCH	GARCH-M	EGARCH			APARCH			GJR		
Distribution	Normal	Normal	Normal	Stud t	Skw Stud t	Normal	Student t	Skw Stud t	Normal	Stud t	Skw Stud t
Order (p, q)	GARCH (1,1)	GARCH-M (1,1)	EGARCH (**)	EGARCH (**)	EGARCH (**)	APARCH (**)	APARCH (**)	APARCH (**)	GJR (2,1)	GJR (**)	GJR (**)
AIC	6.525274	6.520997	**	**	**	**	**	**	6.499961	**	**
SIC	6.556230	6.559693	**	**	**	**	**	**	6.546396	**	**

Stud t means Student t-distribution

Skw Stud t means Skewed Student t-distribution

4.3. Model diagnostic tests

Diagnostic checks are performed on the 23 established models for serial correlation, ARCH effects and normality. The diagnostic tests results show no serial correlation and ARCH effects in the models. A plot of the raw series together with the conditional variance for each model has been examined and volatility clustering exhibits in each case. Nevertheless, a plot of the histogram of the standardized residuals indicate that some of the models (BRT, OCE and AVI) the model errors are approximately normally distributed, but AEE and SHH are not.

4.4. Measuring model forecasting performance on the conditional mean and variance

The performance measures, MAE, MSE, MedSE, RMSE and TIC were applied to all the 23 models to judge on the forecasting ability of the models as well to make a selection of the preferred models. The resultant models were ranked according to the 30-day, 60-day, 90-day, 120-day and 360-day forecasting evaluation measures MAE, MSE, MedSE, AMAPE and TIC for each of the stocks. The forecasting evaluation tests are performed and the ranked model results are cross-validated.

4.5. Cross-validation

Cross-validation is a statistical method for evaluating and comparing learning algorithms by dividing data into two segments, that is, a set used to learn or train a model (train set) and the other set used to validate the model (test set). Hyndman (2014), Goodwin (2012) and Borra and Ciaccio (2010) advocate for cross-validation of forecasting evaluation measures. In this study, cross-validation is performed for two major reasons, firstly; to estimate performance of the learned model from available data using one algorithm in order to gauge the generalizability of an algorithm. Secondly, cross-validation in this study is also intended to compare the performance of two or more variants of the parameterized model for the available data. The forecast error measures from the different train and test sets are cross-validated to establish the best model. The final results of the cross-validated models are compared to the results of the SPA and MCS tests before selection of the final models. The BRT stock has been excluded in this test procedure as it appears clear that the EGARCH (6,5) is carrying much smaller forecast error measures than its counterparts in all the categories of measures applied, that is, MSE, MedSE, MAE, RMSE and TIC. Therefore, EGARCH (6,5) is preferred to other models as a superior model.

4.5.1. Results of Cross-validation of OCE models

In the comparison of the models based on forecasting performance evaluation measures, a distinction is made between the group of measures which are scale-dependent and prone to outliers (MSE and MAE) and those which are not (RMSE, MedSE and TIC). The forecast error estimates data for all the competing models for OCE stock, over the 30, 60, 90, 120 and 360-day forecast periods are examined, to which a comparative discussion of the results is given. Firstly, it is evident that the scale-dependent measures, particularly, MSE show high error values in each forecast horizon. The MSE measure for both the mean and variance forecast indicates that it is more influenced by the effect of scale and outliers than the MAE. Based on the cross-validation results, the APARCH (3,1) and GARCH (1,1) appear to be the best models for forecasting OCE stock. The results of the GARCH (1,1) and APARCH (3,1) have more accurate forecasts for both the shorter and longer forecast period compared to their counterparts. The forecast errors of GARCH (1,1) and APARCH (3,1) do not show significant difference in the long-run, but the results show that the APARCH model show a very slight improvement relative to the GARCH (1,1) with a longer horizon. It is not very clear which of the models improves estimation accuracy, between GARCH (1,1) and APARCH (3,1), in the short- and long-term, thus the GARCH (1,1) model is therefore preferred for its parsimony.

4.5.2. Results of Cross-validation of AEE models

Although the GARCH (1,1) model achieves quite good forecasts error values starting from 30-day till the 360-day forecast period, the EGARCH (2,1) and GJR (5,2) results significantly improve in a longer forecast period. When all the forecast errors are cross-validated, the results of EGARCH (2,1) become more superior than those of the GJR (5,2) model. The results of the cross-validation suggest the choice of the EGARCH (2,1) for the forecast of AEE stock.

4.5.3. Results of Cross-validation of AVI models

The forecasting error estimates of the GARCH (1,1) and GARCH-M (1,1) for the 120-day and 360-day period are very poor in comparison to the asymmetric models' results. This suggests high degree of asymmetry in the AVI stock behaviour. The GJR (3,2) competes with the EGARCH (2,3) and APARCH (1,2) in the short-run but its results become poor as the forecast period increases. The EGARCH (2,3) stands out when compared with the other models in making long-range forecasts of the AVI stock as evidenced in the forecasts from 90-day period going further into the future.

4.5.4. Results of Cross-validation of SHH models

The only optimal models obtained for SHH, which are being compared, are GARCH (1,1) and GARCH-M (1,1). The forecast error measures for the variance in the SHH stock show very large values which further rise with long period forecasts. The stock indicates very high volatility, and the data set for SHH exhibit significant outliers. The GARCH-M (1,1) attains relatively better forecasting error results than the GARCH (1,1) in the short-run. However, the GARCH (1,1) results become far superior in the long-run. The results suggest the application of the GARCH (1,1) model in forecasting the volatility of SHH stock.

4.5.5. Summary of performance evaluation measures and cross-validation results

The cross-validation procedure indicated the models which appear superior to their counterparts in instances where the error measures appear to be inconclusive. According to results of the five performance evaluation measures together with the cross-validation procedure, the EGARCH model appears relatively superior for the stocks BRT, AEE and AVI. GARCH (1,1) is the best model for forecasting OCE and SHH stocks. In general, the key observation from the results is that the asymmetric models, with student t-distribution, tend to perform better with long range forecasts. This is probably a result of the leverage effect in the fishing stocks. A further investigation of the superiority of the models is necessary to test if the models established using the cross-validation approach really outperform their counterparts. The test of superiority, in this study, invokes the SPA and MCS tests outlined in the methodology section. The results of the SPA and MCS tests are given in Section 4.6. below.

4.6. Results of model predictive superiority tests: SPA and MCS

The process of conducting the SPA and MCS tests is performed as follows. Firstly, the loss data for the stocks being tested, that is AEE, AVI, and OCE, is obtained for all the five GARCH models being applied, for four forecast horizons (30 days, 60 days, 90 days, and 120days).

4.6.1. Superior Predictive Ability (SPA) test results

As outlined in the methodology section, the SPA test examines whether any model in a set of models can outperform a benchmark. The test applies three type of p-values used in the test: lower, consistent, and upper. The p-values of the SPA test depend on re-centering of the losses. In all the cases, the consistent p-values is selected and the Null is rejected when p-values are less than 0.05. In each of the cases, the Null hypothesis tested and the alternative are given by:

H_0: $\mu_k \leq 0$ versus H_A: $\mu_k > 0$.

The test is based on 5000 bootstrap replications. In the SPA test process for the AEE stock for all forecast horizons (30,60,90 and 120), GARCH (1,1) is applied as the benchmark model, assuming normal distribution. The SPA test results (p-values), using GARCH (1,1) as the benchmark model assuming normal distribution, obtained using the Python software package are illustrated in Table 4.6. below:

Table 4.6: SPA results for AEE, AVI and OCE

p-value	AEE				AVI				OCE			
	Forecast horizon (Days)				Forecast horizon (Days)				Forecast horizon (Days)			
	30	60	90	120	30	60	90	120	30	60	90	120
Lower	.09	.483	.148	.093	.325	.401	.377	.476	.468	.384	.467	.430
Consistent	.09	.483	.148	.093	.324	.401	.377	.510	.564	.535	.506	.467
Upper	.09	.483	.148	.093	.324	.401	.377	.510	.564	.535	.506	.467

Summary of the SPA test results

Results for all the forecast horizons (30, 60, 90, 120 days) for the three stocks, that is; AEE, AVI and OCE, suggest that the Null is not rejected at 5% level of significance. Accepting the Null implies that there is at least one model in the competing model set that significantly outperforms the benchmark, in each forecast horizon. This indication by SPA results, that there exists at least one model in the competing which might outperform the applied benchmark, calls for a further test to identify the best performing model and other models which are not statistically different from the best performing model. The MCS test can, in this case, be applied to establish the best performing model, by ranking of the entire model set. The results of the MCS procedure carried on the OCE, AEE and AVI competing models are outlined in section 4.6.2 below.

4.6.2. MCS results

The MCS test proposed by Hansen et al. (2011) becomes vital in determining the best model by ranking all the models. The MCS approach takes a set of loss functions as its input and finds the set which are not statistically different from each other while controlling the familywise error rate. The primary output is a set of p-values, where models with a p-value above the size are in the MCS. Small p-values indicate that the model is easily rejected from the set that includes the best.

In this study, all the 45 GARCH models competing are compared simultaneously using Hansen et al. (2011) algorithm. Then, the MCS procedure of Hansen et al. (2011) is applied on each of the datasets with competing models (AEE, AVI, and OCE) to obtain the set of models with superior predictive ability in term of the loss functions given by $(y_{t+h} - \hat{y}_{t+h})^2$.

To demonstrate the MCS results, Table A1 in Appendix A reports the combinations of the superior set of models for AEE 30-day forecast, discriminating by model, distribution and sample period.

Summary of the MCS test results for AEE, AVI and OCE

According to the results of the test of AEE dataset in Table A1 (Appendix A), EGARCH model with Student t-distribution performs best in the short period (30 days) than the rest of the models, followed by EGARCH with skewed t-distribution. It can also be noted, based on the model loss values, that the EGARCH with Skewed Student t and normal density functions are not significantly different from the EGARCH with t-distribution. The poor performing model is the GJR-GARCH with normal distributions.

The first column of Table A1 exhibits the ordered superior models based on the "T-max" statistic. The second column (Rank_M) gives the rank of each model. The superior model (EGARCH, t-distribution) is accorded a rank of 1, while the worst model has the last rank. The third column (V_M) reports the T-max Statistics. The fourth column (MCS_M) reports the number of possible alternative models, which is 1 throughout. Fifth column exhibits Rank_R, that is the ranking of model based on the test statistic "R". In this study, the test statistic "T-max" is applied. Therefore column 5, 6, and 7 of the table are ignored for interpretation since they use alternative statistics. Column 6 (V_R) shows the test statistics of each model based on the R statistic. Column 7 (MCS_R) reports similar statistic as (MCS_M). Therefore, EGARCH (2,1) under t-distribution is the superior model in the short-run for the company AEE. Tables A1 to Table A12 in Appendix A illustrate the results of the MCS tests for AEE, AVI and OCE, indicating the best model, in the short run and long-run. In the 60-day forecast of the AEE stock, the GJR distribution, assuming student distribution, achieves the best forecast. The GJR model with normal and Skewed Student t-distribution are not significantly different from the superior model in the set. The second-best model is the GJR with normal distribution. The worst model is the GARCH-M (1,1) based on the Skewed Student t density function. The summary analysis of the superiority of the models in prediction is provided.

The MCS test results, over all the tested forecast horizons, reveal that the AEE stock can be best forecast by the GJR in the short-run. The EGARCH with t-distribution emerges as the superior model in the longer horizon. Since the comparison of the forecast error measures indicated very small differences in short-run performance, the EGARCH model is preferred to the GJR in the modelling of AEE since it generally performs better.

The EGARCH model is superior in both the short and long-term forecasting of the AVI stock, although the GJR also does improve in the long-run forecasting performance. The results also show that the performance of the AVI stock is best modelled with fat tails.

The best model for modelling and forecasting is the GARCH (1,1) with the normal distribution. The GJR model performs well in the 30-day period. The EGARCH (1,1) also estimates the OCE stock accurately. However, the GARCH (1,1) is dominant when all the forecast horizons are considered. Therefore, the GARCH (1,1) is selected for the forecasting of OCE. Following the SPA and MCS tests, summary statistics and graphical of the distributional features of the stocks (AEE, AVI and OCE) are examined.

Table 4.7: Summary of variance forecasting performance evaluation measures of the superior models

Stock	Model selected	Distribution	Forecast Period	MSE (VAR)	MedSE (VAR)	MAE (VAR)	RMSE (VAR)	TIC (VAR)
Brimstone (BRT)	EGARCH (6,5)	Student t	30-day	8.322	8.285	2.846	2.885	0.7679
			60-day	34.17	27.13	5.119	5.845	0.6016
			90-day	76.03	16.41	5.148	8.72	0.6562
			120-day	74.02	3.065	3.573	8.604	0.7747
			360-day	45	0.8494	2.203	6.708	0.8437
Oceana (OCE)	GARCH (1,1)	Normal	3o-day	92.43	10.66	5.742	9.614	0.6779
			60-day	157.5	11.85	6.698	12.55	0.7112
			90-day	171.6	10.33	6.45	13.1	0.7404
			120-day	132.5	11.24	5.775	11.51	0.7103
			360-day	251.2	9.339	5.48	15.85	0.7947
Premier Fishing (AEE)	EGARCH (2,1)	Skewed Student t	30-day	6.198	0.3875	1.265	2.49	0.7126
			60-day	4.015	0.5023	1.111	2.004	0.6379
			90-day	4.975	0.3891	1.203	2.23	0.6572
			120-day	4.882	0.4482	1.278	2.209	0.6478
			360-day	7.648	0.1703	1.321	2.766	0.7979
Irvin & Johnson (AVI)	EGARCH (2,3)	Student t	30-day	196.5	36.98	9.809	14.02	0.5869
			60-day	126.5	16.72	7.024	11.25	0.6338
			90-day	89.77	19.29	6.076	9.475	0.5822
			120-day	75.24	18.54	5.614	8.674	0.5719
			360-day	94.5	12.27	4.824	9.721	0.656
Sea Harvest (SHH)	GARCH (1,1)	Normal	30-day	1825	926.6	36.17	42.72	0.6601
			60-day	5281	3239	62.78	72.67	0.7018
			90-day	24100	15670	136.7	155.2	0.835
			120-day	608500	301500	655.4	780	0.9168
			360-day	47790	15410	144.7	218.6	0.6195

4.7. Specifications and tests of the final selected models

The final selected models for each firm are specified in the Tables 4.8, 4.10, 4.12, 4.14 and 4.16. The selected models are also tested for the existence of serial correlation, ARCH effects and normality, shown in Tables 4.9, 4.11, 4.13, 4.15 and 4.17.

4.7.1. OCE final model

Table 4.8: OCE GARCH (1,1)

The dependent variable is:	OCE Daily Stock Returns
Mean Equation:	ARMA (1, 0) model
No regressor in the conditional mean	
Variance Equation:	GARCH (1, 1) model
No regressor in the conditional variance	
Normal distribution	
Strong convergence using numerical derivatives	
Log-likelihood = -7709.96	

Robust Standard Errors (Sandwich formula)

	Coefficient	Std.Error	t-value	t-prob
Cst(M)	0.043500	0.026629	1.634	0.1024
AR(1)	-0.086423	0.025588	-3.377	0.0007
Cst(V)	0.536891	0.201660	2.662	0.0078
ARCH(Alpha1)	0.138472	0.138472	3.843	0.0001
GARCH(Beta1)	0.708888	0.082525	8.590	0.0000

No. Observations:	3909	No. Parameters:	5
Mean (Y):	0.06569	Variance (Y):	3.50594
Skewness (Y):	0.03358	Kurtosis (Y):	17.16817
Log Likelihood:	-7709.959	Alpha [1] + Beta [1]:	0.84736

The sample mean of squared residuals was used to start recursion.

The positivity constraint for the GARCH (1,1) is observed.

This constraint is alpha[L]/ [1 - beta(L)] >= 0.

The unconditional variance is 3.51737

The conditions are alpha [0] > 0, alpha[L] + beta[L] < 1 and alpha[i] + beta[i] >= 0.

The condition for existence of the fourth moment of the GARCH is observed.

The constraint equals 0.756368 and should be < 1.

Estimated Parameters Vector:

0.043500; -0.086423; 0.536891; 0.138472; 0.708893

OCE post-estimation tests:

Tests for normality, serial correlation and ARCH effects of OCE stock are indicated in Table 4.9 below:

Table 4.9: OCE normality, serial correlation and ARCH effects test

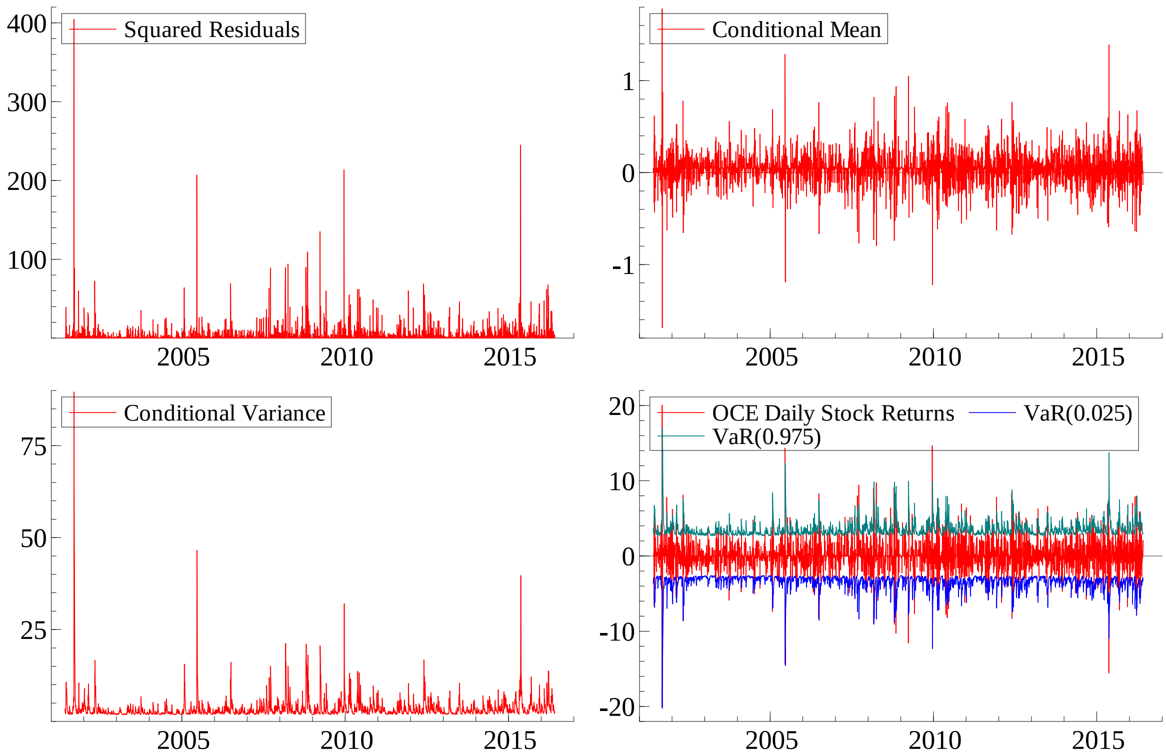
Normality test			
	Statistic	t-Test	P-Value
Skewness	-0.030114	0.76893	0.44193
Excess Kurtosis	9.5219	121.60	0.00000
Jarque-Bera	14768.	. NaN	0.00000
Serial correlation test			
Q-Statistics on Squared Standardized Residuals			
P-values adjusted by 2 degree(s) of freedom			
Q (5) =	0.904931	[0.8242377]	
Q (10) =	3.50533	[0.8987754]	
Q (20) =	7.09948	[0.9892603]	
Q (50) =	46.7303	[0.5249124]	
H0: No serial correlation			
Accept H0 when prob. is High [Q < Chisq(lag)]			
ARCH LM test			
ARCH 1-2 test:	F (2,3902) =	0.14777	[0.8626]
ARCH 1-5 test:	F (5,3896) =	0.17997	[0.9702]
ARCH 1-10 test:	F (10,3886) =	0.33737	[0.9712]

Using Q-Statistics test with 50 lags, the test for serial correlation on OCE model indicate that the Null of no serial correlation in the OCE model cannot be rejected at 5% level since all the p-values for the statistics are insignificant. Again, the test of ARCH effects with 10 lags reflect that all the statistics are insignificant at 5% level of significance. Therefore, the Null hypothesis of no ARCH effects cannot be rejected. However, the Jarque-Bera statistic is significant suggesting the data is not normal at 5% level of significance.

The graphs of the squared residuals, conditional mean and conditional variance for each of the stocks, based on the optimal models, are plotted to investigate the general behaviour of the swings of the fishing stocks. The squared residuals, conditional mean and variances of

OCE are illustrated in Figure 4.1 below:

Figure 4.1: Plot of OCE squared residuals, conditional mean and conditional variance



The plot of the squared residuals, conditional mean and conditional variance of OCE above indicates volatility clustering, that is, periods of high volatility are followed by periods of high volatility and also periods of low volatility are followed by periods of low volatility. It is notable that in the period towards 2010, that is, between 2008 and 2009, the market was very noise. The volatility swings of the stock are also significant in the early 2000, mid 2005 and early 2015. A plot of the 95% limits of the stock returns indicates the periods with the most significant outliers. The plot of the squared residuals, conditional mean and conditional variance for the other firms are indicated in Appendix B (Figures B1, B2, B3, B4 and B5).

4.7.2. BRT final model

Table 4.10: BRT EGARCH (6,5)

The dependent variable is:	BRT Daily Stock Returns			
Mean Equation:	ARMA (1, 0) model			
No regressor in the conditional mean				
Variance Equation:	EGARCH (6, 5) model			
No regressor in the conditional variance				
Student distribution, with 2.74218 degrees of freedom				
Weak convergence (no improvement in line search) using numerical derivatives				
Log-likelihood = -6718.56				
Robust Standard Errors (Sandwich formula)				
	Coefficient	Std.Error	t-value	t-prob
Cst(M)	0.043760	0.01240	3.529	0.0004
AR(1)	-0.078153	0.01755	-4.453	0.0000
Cst(V)	0.130452	0.45899	0.284	0.7763
ARCH(Alpha1)	1.057605	0.24344	4.344	0.0000
ARCH(Alpha2)	-0.462211	0.34971	-1.322	0.1863
ARCH(Alpha3)	-0.482607	0.24546	-1.966	0.0494
ARCH(Alpha4)	-0.360558	0.29840	-1.208	0.2270
ARCH(Alpha5)	-0.404294	0.17593	-2.298	0.0216
GARCH(Beta1)	-0.457229	0.21967	-2.081	0.0375
GARCH(Beta2)	1.116828	0.23604	4.732	0.0000
GARCH(Beta3)	0.433860	0.33960	1.278	0.2015
GARCH(Beta4)	0.239701	0.34369	0.697	0.4856
GARCH(Beta5)	0.027452	0.14888	0.184	0.8537
GARCH(Beta6)	-0.361565	0.12558	-2.879	0.0040
EGARCH(Theta1)	0.013468	0.03243	0.415	0.6780
EGARCH(Theta2)	0.754256	0.06437	11.720	0.0000
Student(DF)	2.742180	0.13084	20.960	0.0000

No. Observations:	3771	No. Parameters:	17
Mean (Y):	-0.00599	Variance (Y):	6.60947
Skewness (Y):	1.07832	Kurtosis (Y):	33.17164
Log Likelihood:	-6718.563		

Estimated Parameters Vector:					
0.043760;	-0.078153;	0.130452;	1.057605;	-0.462211;	-0.482607;
-0.360558;	-0.404294;	-0.457229;	1.116828;	0.433860;	0.239701;
0.027452;	-0.361565;	0.013468;	0.754256;	2.74218	

BRT post-estimation tests:

The results of the tests for normality, serial correlation and ARCH effects for BRT stock are illustrated below:

Table 4.11: BRT normality, serial correlation and ARCH effects test

Normality test			
	Statistic	t-Test	P-Value
Skewness	0.50706	12.717	4.7607e-037
Excess Kurtosis	9.2134	115.57	0.00000
Jarque-Bera	13500.	. NaN	0.00000
Serial correlation test			
Q-Statistics on Squared Standardized Residuals			
P-values adjusted by 11 degree(s) of freedom			
Q (20) =	12.2348	[0.2003922]	
Q (50) =	23.1631	[0.9792548]	
H0: No serial correlation			
Accept H0 when prob. is High [Q < Chisq(lag)]			
ARCH LM test			
ARCH 1-2 test:	F (2,3755) =	1.1120	[0.3290]
ARCH 1-5 test:	F (5,3749) =	0.54317	[0.7437]
ARCH 1-10 test:	F (10,3739) =	0.48844	[0.8986]

In the test for serial correlation with 50 lags, all the p-values for the Q-Statistics are insignificant suggesting that the Null of no serial correlation in the BRT model cannot be rejected at 5% level. BRT ARCH effects test with 10 lags reflect that all the statistics are insignificant at 5% level of significance. Therefore, the Null hypothesis of no ARCH effects also cannot be rejected. On normality test, the Null hypothesis that the data is normally distributed is rejected at 5% level of significance since the p-value is approximately zero. Therefore, the BRT model satisfies the key assumptions required and is adopted for application in forecasting the BRT stock volatility.

4.7.3. AEE final model

Table 4.12: AEE EGARCH (2,1)

The dependent variable is:	AEE Daily Stock Returns			
Mean Equation:	ARMA (1, 0) model			
No regressor in the conditional mean				
Variance Equation:	EGARCH (2, 1) model			
No regressor in the conditional variance				
Skewed Student distribution, with 7.58786 degrees of freedom				
and asymmetry coefficient (log xi) -0.115468.				
Strong convergence using numerical derivatives				
Log-likelihood = -5716.17				
Robust Standard Errors (Sandwich formula)				
	Coefficient	Std.Error	t-value	t-prob
Cst(M)	0.007357	0.014984	0.491	0.6234
AR(1)	-0.022112	0.014912	-1.483	0.1382
Cst(V)	-1.097039	0.309890	-3.54	0.0004
ARCH(Alpha1)	-0.836291	0.092884	-9.004	0.0000
GARCH(Beta1)	1.683543	0.150620	11.18	0.0000
GARCH(Beta2)	-0.688172	0.147990	-4.65	0.0000
EGARCH(Theta1)	-0.061411	0.017735	-3.463	0.0005
EGARCH(Theta2)	0.232131	0.037178	6.244	0.0000
Asymmetry	-0.115468	0.023854	-4.841	0.0000
Tail	7.58786	0.99074	7.659	0.0000

No. Observations:	3771	No. Parameters:	10
Mean (Y):	0.00304	Variance (Y):	1.81021
Skewness (Y):	-0.62192	Kurtosis (Y):	22.83097
Log Likelihood:	-5716.174		

Estimated Parameters Vector:
0.007357; -0.022112; -1.097039; -0.836291; 1.683543; -0.688172;
-0.061411; 0.232131; -0.115468; 7.587865

AEE post-estimation tests:

AEE results of the tests for normality, serial correlation and ARCH effects are demonstrated below in Table 4.13.

Table 4.13: AEE normality, serial correlation and ARCH effects test

Normality test			
	Statistic	t-Test	P-Value
Skewness	-0.71769	18.000	1.9616e-072
Excess Kurtosis	5.8975	73.974	0.00000
Jarque-Bera	5788.6	. NaN	0.00000
Serial correlation test			
Q-Statistics on Squared Standardized Residuals			
P-values adjusted by 3 degree(s) of freedom			
Q (5) =	0.630448	[0.7296255]	
Q (10) =	1.98843	[0.9604779]	
Q (20) =	4.40415	[0.9990177]	
Q (50) =	11.1579	[1.0000000]	
H0: No serial correlation			
Accept H0 when prob. is High [Q < Chisq(lag)]			
ARCH LM test			
ARCH 1-2 test:	F (2,3763) =	0.13929	[0.8700]
ARCH 1-5 test:	F (5,3757) =	0.12679	[0.9864]
ARCH 1-10 test:	F (10,3747) =	0.19992	[0.9963]

None of the Q-Statistics for the AEE model are significant when tested with 50 lags which implies that the Null hypothesis of no serial correlation in the AEE model cannot be rejected at 5% level. The test of ARCH effects with 10 lags indicate that the Null cannot be dismissed at 5% level of significance. The Jarque-Bera statistic has a p-value close to zero suggesting that the data is not normal at 5% level of significance.

4.7.4. AVI final model

Table 4.14: AVI EGARCH (2,3)

The dependent variable is:	AVI Daily Stock Returns			
Mean Equation:	ARMA (1, 0) model			
No regressor in the conditional mean				
Variance Equation:	EGARCH (2, 3) model			
No regressor in the conditional variance				
Student distribution, with 3.20738 degrees of freedom				
Weak convergence (no improvement in line search) using numerical derivatives				
Log-likelihood = -7609.93				
Robust Standard Errors (Sandwich formula)				
	Coefficient	Std.Error	t-value	t-prob
Cst(M)	0.08810	0.01380	6.38300	0.00000
AR(1)	-0.09678	0.01372	-7.05300	0.00000
Cst(V)	1.53630	0.18273	8.40700	0.00000
ARCH(Alpha1)	0.25101	0.06972	3.60000	0.00030
ARCH(Alpha2)	-0.60490	0.05422	-11.16000	0.00000
ARCH(Alpha3)	-0.01783	0.07484	-0.23820	0.81180
GARCH(Beta1)	0.03986	0.02053	1.94200	0.05220
GARCH(Beta2)	0.92152	0.02082	44.26000	0.00000
EGARCH(Theta1)	0.04318	0.02457	1.75700	0.07900
EGARCH(Theta2)	0.60364	0.04522	13.35000	0.00000
Student(DF)	3.20738	0.20507	15.64000	0.00000
No. Observations:	3878	No. Parameters:	11.00000	
Mean (Y):	0.0576	Variance (Y):	8.75584	
Skewness (Y):	-0.45121	Kurtosis (Y):	4.4371	
Log Likelihood:	-7609.934			

Estimated Parameters Vector:					
0.088098;	-0.096783;	1.536304;	0.251008;	-0.604904;	-0.017826;
0.039862;	0.921524;	0.043180;	0.603636;	3.207384	

AVI post-estimation tests:

The tests for normality, serial correlation and ARCH effects of the AVI stock show in Table 4.15 below.

Table 4.15: AVI normality, serial correlation and ARCH effects test

Normality test			
	Statistic	t-Test	P-Value
Skewness	-0.19013	4.8355	1.3284e-006
Excess Kurtosis	14.265	181.44	0.00000
Jarque-Bera	32903.	. NaN	0.00000
Serial correlation test			
Q-Statistics on Squared Standardized Residuals			
P-values adjusted by 5 degree(s) of freedom			
Q (10) =	5.79638	[0.3265391]	
Q (20) =	32.9715	[0.0047366] **	
Q (50) =	42.6222	[0.5732030]	
H0: No serial correlation			
Accept H0 when prob. is High [Q < Chisq(lag)]			
ARCH LM test			
ARCH 1-2 test:	F (2,3868) =	0.47232	[0.6236]
ARCH 1-5 test:	F (5,3862) =	0.25660	[0.9366]
ARCH 1-10 test:	F (10,3852) =	0.59429	[0.8199]

The Q-Statistics test indicate that there is no serial correlation in the resultant AVI model at 5% level since all the p-values for the statistics are insignificant. The ARCH LM test results in insignificant statistics hence, at 5% level of significance, the Null of no ARCH effects in the model will not be rejected. The Jarque-Bera statistic is again significant suggesting the data is not normal at 5% level of significance.

4.7.5. SHH final model

Table 4.16: SHH GARCH (1,1)

The dependent variable is: SHH Daily Returns
Mean Equation: ARMA (1, 0) model
No regressor in the conditional mean
Variance Equation: GARCH (1, 1) model
No regressor in the conditional variance
Normal distribution
Strong convergence using numerical derivatives
Log-likelihood = -1791.19

Robust Standard Errors (Sandwich formula)

	Coefficient	Std.Error	t-value	t-prob
Cst(M)	0.104109	0.24153	0.431	0.6666
AR(1)	-0.373236	0.070368	-5.304	0.000
Cst(V) x 10^4	11806.20213	110100	1.072	0.284
ARCH(Alpha1)	0.160634	0.064469	2.492	0.013
GARCH(Beta1)	0.83687	0.053429	15.66	0.000

No. Observations:	559	No. Parameters:	5
Mean (Y):	-0.38493	Variance (Y):	100.57337
Skewness (Y):	-0.37332	Kurtosis (Y):	23.76519
Log Likelihood:	-1791.189	Alpha [1] + Beta[1]:	0.9975

The sample mean of squared residuals was used to start recursion.
The positivity constraint for the GARCH (1,1) is observed.
This constraint is alpha[L]/ [1 - beta(L)] >= 0.
The unconditional variance is 472.928
The conditions are alpha [0] > 0, alpha[L] + beta[L] < 1 and alpha[i] + beta[i] >= 0.
The condition for existence of the fourth moment of the GARCH is not observed.
The constraint equals 1.04662 and should be < 1.

Estimated Parameters Vector:
0.104109; -0.373236; 11806.202130; 0.160634; 0.836875

SHH post-estimation tests:

Model post-estimation test results are given in Table 4.17.

Table 4.17: SHH normality, serial correlation and ARCH effects test

Normality test			
	Statistic	t-Test	P-Value
Skewness	0.36996	3.5806	0.00034286
Excess Kurtosis	15.333	74.328	0.00000
Jarque-Bera	5488.6	. NaN	0.00000
Serial correlation test			
Q-Statistics on Squared Standardized Residuals			
P-values adjusted by 2 degree(s) of freedom			
Q (5) =	2.91169		[0.4054418]
Q (10) =	4.58966		[0.8003977]
Q (20) =	6.87949		[0.9911038]
Q (50) =	30.9721		[0.9731983]
H0: No serial correlation			
Accept H0 when prob. is High [Q < Chisq(lag)]			
ARCH LM test			
ARCH 1-2 test:	F (2,552) =	0.97542	[0.3777]
ARCH 1-5 test:	F (5,546) =	0.35008	[0.8822]
ARCH 1-10 test:	F (10,536) =	0.40427	[0.9447]

The Q-Statistics in the test of serial correlation in the SHH model are insignificant, at 5% level, meaning H_0 can not be rejected. The ARCH LM test indicate no ARCH effects in the final model, at 5% level of significance. The Jarque-Bera has a p-value which is close to zero which implies that the data is not normal at 5% level of significance.

Summary of the residuals, conditional mean and conditional variance for fishing stocks

In general, the plots of the squared residuals, the conditional mean and the conditional variance for all the fishing stocks exhibit the highest noise effect in the years between 2001 and 2004. The sector also indicates significant noise during the period of the global financial crisis, that is, between the middle of 2007 and end of year 2009. The year 2012, 2014 and 2015 are also marked by high volatility. However, in general, the volatility of the entire industry indicates a significant drop over the years. There is a concord between this evidence and the evidence in the reviewed literature in which the use of diversification, improved fish stock assessment and other methods are stressed as factors improving industry stability.

4.8. Volatility forecasts

The forecasts of volatilities for the future 360-day period for each of the stocks under study are estimated. The plots of the volatility forecasts for each of the stocks, together with the 90% bound of the forecasts for BRT, OCE, AEE and AVI are illustrated in Appendix C. The general observation from the forecast results is that the short-run conditional variance of the fishing stocks is expected to drop to a low long-run unconditional variance. The 360-day volatility forecast of BRT shows that the conditional variance of BRT returns to its unconditional variance of about 1.5 after a long time. The stock shows high degree of noise in the short-run which lasts for a long time. The 90% confidence bounds (lower and upper) of the short-run volatility are close -1.5 and 1.5, respectively. For OCE, the long-run volatility is around 3.6. The stock generally takes short period of time to return to its long-run level given any shock. The AEE stock's 360-day volatility forecast is quite high in the short-term but drops to a very low long-run level of 0.2. AVI shows the highest short-term volatility which also significantly drops in the long-run to a level of 5.0.

4.9. Estimating annual volatility estimates from daily volatilities

Financial theory commonly characterizes the behavior of return series of stocks with the Wiener process (Random Walk) in which a fund is assumed to evolve randomly with time, with a finite variance. In view of that feature, the formula applied in the estimation of annualized volatility of the fishing stocks from daily volatility measures is stated as follows:

$$\sigma = \frac{\sigma_D}{\sqrt{T}} \quad \cdots \tag{34}$$

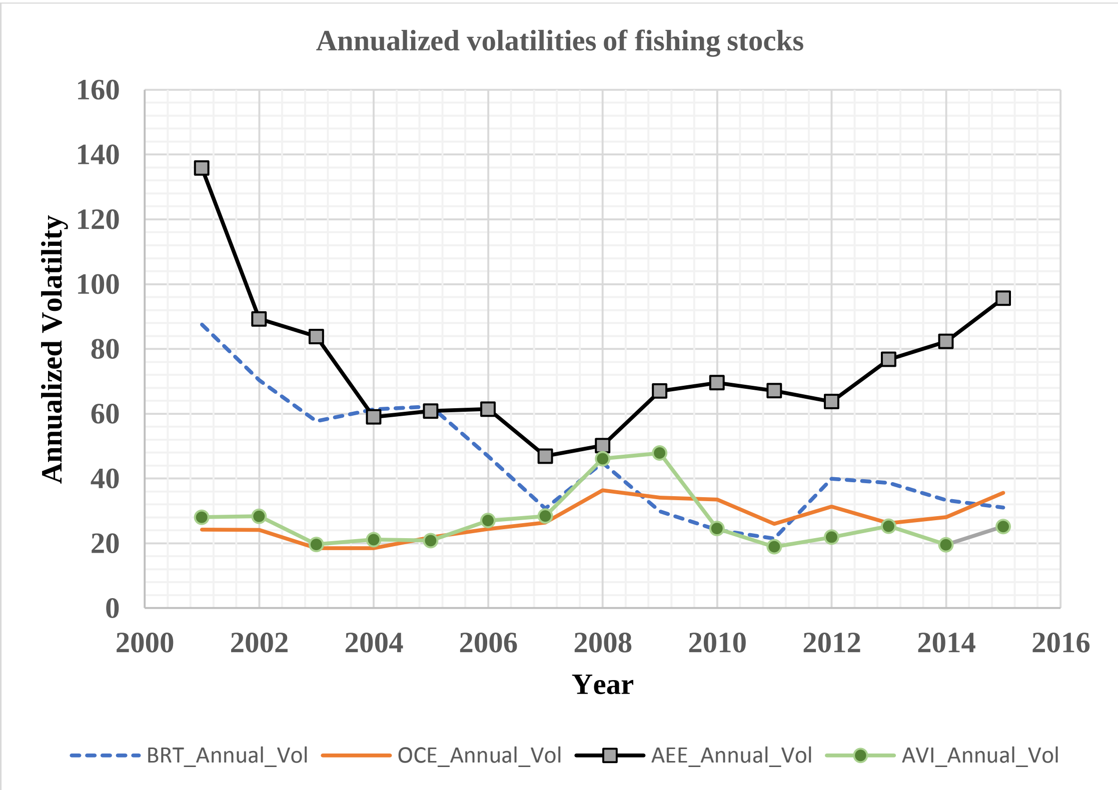
where σ_D is the standard deviation of the daily logarithmic returns of stock (or daily volatility), σ is the annualized volatility and T=1/252.

The value T=1/252 is used since common assumption in most financial markets is that there are 252 trading days in any given year.

4.10. Plot of annualized volatilities: BRT, OCE, AEE, AVI

A plot of the time series of annualized volatilities gives the patterns of each individual stocks which are consistent with observations on the daily stocks. The graphs of the annualized data are indicated in Figure 4.2 below:

Figure 4.2: Annualized volatilities



The plot above (Figure 4.2) over the 15-year period shows that AEE stock experiences the highest volatility over the entire period under study. BRT stock has had high volatility in early 2000 but its trajectory indicates a high improvement in stability. The AVI and OCE are relatively stable stocks, when compared to BRT and AEE.

4.11. Estimation of the Vector Autoregressive (VAR) model

In the estimation of the VAR model, the dependent variable is the volatility, which was modelled as a function of four dependent variables, namely; earnings per share (EPS), Net-worth (NW), margin of safety (MOS) and free cash flow (FCF). The panel of companies in question generally have similarities evidenced from the fact that no outlier effects are detected based on the tests.

4.11.1. Preliminary hypothesis tests

Prior to the estimation of the VAR model, an investigation of the conditions required for VAR model to be valid was carried out. The tests include the Group Unit Root and Granger-causality tests. The p-value of the Group Unit Root test is 0.0005 dismisses the Null hypothesis of the existence of unit root. However, tests for normality, ACRH effects and serial correlation are first performed. The results confirmed existence of ARCH effects, serial correlation but lack of normality. The results of the Unit Root test are reflected in Table D1 of Appendix D.

According to the results of the test, the Null hypothesis of unit root at level is rejected using 5% level of significance. Therefore, all the series (BRT, OCE, AEE, AVI) are assumed to be stationary and satisfy one of the key conditions necessary for the application of VAR model.

4.11.2. Granger-causality test

The result of pairwise Granger-causality test suggests the non-existence of causal effect on the volatility by FCF, MOS, NW, and EPS. However, unidirectional Granger-causality is observed on NW from volatility at 10% level of significance.

4.11.3. VAR model estimation

The Restricted-VAR model is estimated as a function of the independent variables; EPS, NW, MOS and FCF including the lags of the dependent and the independent variables.

Table 4.18: VAR regression estimates

Sample (adjusted): 3 60 Included observations: 58 after adjustments

	VOL	MOS	FCF	NW	EPS
VOL (-1)	0.737521	-256.7056	-264.1866	-788.6671	-1.133208
	(0.19332)	(408.038)	(180.398)	(782.419)	(1.31728)
	[3.81499]	[-0.62912]	[-1.46446]	[-1.00799]	[-0.86026]
VOL (-2)	-0.005898	-184.5010	61.75198	-259.8758	-0.840417
	(0.18243)	(385.046)	(170.234)	(738.333)	(1.24306)
	[-0.03233]	[-0.47917]	[0.36275]	[-0.35198]	[-0.67609]
MOS (-1)	8.76E-05	0.862394	0.276196	1.114695	0.001184
	(0.00018)	(0.38658)	(0.17091)	(0.74128)	(0.00125)
	[0.47842]	[2.23082]	[1.61601]	[1.50375]	[0.94896]
MOS (-2)	4.51E-05	-0.249229	-0.082630	-0.526243	-0.000952
	(0.00018)	(0.37094)	(0.16400)	(0.71129)	(0.00120)
	[0.25652]	[-0.67188]	[-0.50385]	[-0.73984]	[-0.79507]
FCF (-1)	0.000175	0.381328	0.496788	-0.104922	0.000625
	(0.00019)	(0.40271)	(0.17804)	(0.77221)	(0.00130)
	[0.91760]	[0.94690]	[2.79025]	[-0.13587]	[0.48101]
FCF (-2)	6.21E-05	0.195783	-0.152570	-1.650098	0.000123
	(0.00021)	(0.43671)	(0.19308)	(0.83740)	(0.00141)
	[0.30025]	[0.44831]	[-0.79021]	[-1.97050]	[0.08744]
NW (-1)	6.17E-05	-0.213308	-0.101630	0.156824	-0.001030
	(6.0E-05)	(0.12743)	(0.05634)	(0.24434)	(0.00041)
	[1.02166]	[-1.67398]	[-1.80398]	[0.64182]	[-2.50379]
NW (-2)	-0.000126	0.146427	0.098710	0.626410	0.000618
	(6.3E-05)	(0.13265)	(0.05865)	(0.25436)	(0.00043)
	[-2.00334]	[1.10385]	[1.68313]	[2.46269]	[1.44328]
EPS (-1)	-0.044283	0.172714	-34.39060	-40.92889	0.706297
	(0.04861)	(102.599)	(45.3605)	(196.736)	(0.33123)
	[-0.91099]	[0.00168]	[-0.75816]	[-0.20804]	[2.13237]
EPS (-2)	0.044413	-45.92218	14.02619	-20.55225	-0.130694
	(0.04645)	(98.0374)	(43.3436)	(187.988)	(0.31650)
	[0.95618]	[-0.46841]	[0.32360]	[-0.10133]	[-0.41294]
C	11.24260	44329.77	13518.69	92685.27	193.4522
	(12.5605)	(26511.0)	(11720.8)	(50835.2)	(85.5864)
	[0.89508]	[1.67213]	[1.15339]	[1.82325]	[2.26031]
R-squared	0.472029	0.524124	0.533294	0.678278	0.504500
Adj. R-squared	0.359695	0.422874	0.433995	0.609826	0.399074
Sum sq. resids	18438.53	8.21E+10	1.61E+10	3.02E+11	856097.9
S.E. equation	19.80680	41805.51	18482.74	80162.74	134.9624
F-statistic	4.202001	5.176520	5.370579	9.908884	4.785365
Log likelihood	-249.3893	-693.3653	-646.0262	-731.1251	-360.6896

Akaike AIC	8.978942	24.28846	22.65608	25.59052	12.81688
Schwarz SC	9.369716	24.67923	23.04685	25.98129	13.20766

In the model for volatility, only the second lags of the volatility and FCF are found significant at 5% significance level. The first lag of EPS is significant in the MOS model at 5% level while the second lag of FCF is significant in the EPS at 10%. Also, EPS is significant in the NW at 10%. The model R-squared is 0.472 while adjusted R-squared is 0.360. The joint significance of the variables is also investigated which confirm no joint significance.

4.11.4. VAR model post-estimation test

Post-estimation tests for normality, ARCH effects and serial correlation are also performed. The model is found satisfactory with respect to the three tests. A variance decomposition was performed to identify the variables that contributed most to the volatility of the stock in the short, medium and long-term. The results of the decomposition of variability over 10-year period ahead are shown in Section 4.11.5 below.

4.11.5. The variance decomposition of volatility

Table 4.19: variance decomposition of volatility (10 years) ahead

Period	S.E.	VOL	MOS	FCF	NW	EPS
1	19.80680	100.0000	0.000000	0.000000	0.000000	0.000000
2	23.29277	94.86510	1.377429	0.685693	1.843537	1.228244
3	25.02887	87.92078	5.095958	3.097210	2.395363	1.490688
4	26.16450	82.05322	7.938230	4.677749	3.896011	1.434793
5	27.49823	74.79356	8.652440	9.077323	6.148552	1.328122
6	28.88476	67.92007	8.155795	14.37753	8.261967	1.284635
7	30.08998	62.63040	7.561982	18.82448	9.699403	1.283735
8	31.03487	58.89527	7.121557	22.09826	10.57864	1.306273
9	31.72351	56.37648	6.831441	24.35560	11.09487	1.341607
10	32.21737	54.66518	6.651511	25.90123	11.40266	1.379419

The analysis of the variance decomposition of volatility is done using three time horizons, the short, medium and long-term. In the short-run, for instance, year 2, innovation or shock to

VOL accounts for 94.87% variation of the fluctuation in VOL (own shock), shock to MOS can cause up to 1.38% variation of the fluctuation in VOL, and FCF, NW and EPS will be 0.69%, 1.84% and 1.23% respectively. This implies that the contribution of the lag of volatility is very significant in the short-term. In the medium-term, such as, in year 5, FCF is contributing about 9.077%, MOS contributes 8.652%, NW 6.149%, EPS 1.328% and the rest (74.794%) is contributed by the lag of volatility. This implies that, in the medium-term, the lag of volatility, FCF and pre-tax income (MOS) contribute the larger part to the fluctuation of volatility. In the long-run, for instance, in year 10, a shock in VOL can contribute 54.67% of the total variability in the VOL. The contribution to overall variation due to an impulse on FCF and NW will increase to 25.9% and 11.4% respectively, while that of MOS will be 6.65% and EPS, 1.38%. Therefore, VOL lag, FCF and NW are significant in affecting volatility in the short-term, and MOS becomes quite relatively significant in the medium term while FCF and NW become very significant in the long-run. Overall, it can be observed that, the more recent lags of volatility tend to contribute more to the volatility of the stocks and the volatility has a long memory which agrees to the finance theory regarding equity stocks. By extracting and analysing the changes in the variation sources over the 10-year period, it can be noted that, in general, shocks on FCF of the firm accounts for the largest part of fluctuation in VOL followed by NW and then MOS. This suggests that FCF is the most important factor affecting volatility in returns of the fishing companies in the long-term, followed by NW. The impulse responses of the MOS, FCF, NW and EPS on volatility are examined in Section 4.11.5 below.

4.11.5: Effects of shocks on the independent variables on volatility

In general, the shocks to MOS and FCF positively affect volatility for the whole period ahead (10 years) while shocks to NW and EPS are generally negative for the 10-year period. A shock to the MOS leads to a sharp rise in VOL till the 3^{rd} year before VOL calms down and tends towards a constant positive level. Innovation in FCF generally tends to have a sharp effect on VOL which also lasts longer, and tends to gradually decrease after the 7^{th} year. Equity (NW) innovation immediately causes a positive change in VOL but as soon as in the 2^{nd} year VOL sharply decreases and falls into the negative range, but later tends back towards zero towards the 10^{th} year. Innovation in EPS results in a sharp decrease in volatility until the second year, after which it reverts towards the normal (constant) level but in the negative range.

4.11.6. Robust least squares MM estimation

The Robust Least Squares MM estimation mitigates any effects of outliers. It is shown, from the robust least squares MM estimation, that FCF, NW and EPS negatively affect volatility. Also, NW and EPS are statistically significant at 1% level while the FCF is insignificant. MOS positively affect volatility and is significant at 1% level.

4.12. Interpretation of findings

4.12.1. Relative superiority of predictive models

Firstly, it is observed that the GARCH modelling was more effective when there is relatively long memory, that is, when ACF and PACF exhibit long dependence, as can be observed on the AEE and AVI companies' models. These companies' PACF and ACF show relatively longer dependence than the others and their forecast tests show relatively smaller forecast errors. However, in general, the EGARCH, GARCH (1,1) and APARCH models were relatively better models in estimating the volatility of the fishing sector based on the comparison of forecasting evaluations and the tests superior predictive ability tests. Evidence show that most of the stocks are affected by the factors, FCF, NW and MOS as shown by the VAR model. Volatility of the sector exhibits high persistence as shocks tend to last long.

4.13. Discussion of results

In most of the cases, GARCH (1,1) and GARCH-M (1,1) performed comparatively better in short-term forecasting than their counterparts. The asymmetric models' forecasting performance evaluation measures reduced with an increase in the forecasting horizon. However, there are two cases in which one type of model performed best both in the short and long-term. The first case is that of EGARCH (6,5) in the forecasting of BRT and GACRH (1,1) in the forecasting of SHH. GARCH (1,1) and GARCH-M (1,1) performed well in the short-run forecasts of OCE but APARCH (3,1) emerged the best with an increase in forecast period ahead. Also, EGARCH (2,1) overall outperformed other models in AEE forecasting while EGARCH (2,3) was the best in forecasting AVI, but in both cases GARCH (1,1) and GARCH-M (1,1) short-run forecasts were superior. A general observation from all the firms under study is that EGARCH modelled the fishing sector best. When the forecasting performance evaluation measures of each firm are cross-validated, APARCH (3,1) emerged as the best model in modelling and forecasting OCE, AVI would best be modelled by EGARCH (2,3), AEE by EGARCH (2,1) and SHH by GARCH (1,1). The BRT stock are not cross-validated as it appeared clear from the ranking of the error measures that EGARCH (6,5) is dominant. In forecasting AVI stock, the MCS test indicated that EGARCH (2,3) is the best model in the 30, 60 and 90-day horizons, but only outperformed by GJR (3,2) under student distribution when the horizon increased to 120 days. This means EGARCH does well in the short while GJR does well in the long-run. On the AEE stock, EGARCH (2,1) tends to compete with GJR (5,2) in the short-run but as the horizon widens EGARCH outperforms GJR. It is therefore noted that cross-validation results are consistent with the SPA and MCS test results in the results of AVI and AEE, but tend to differ with the results of OCE. In the OCE stock, MCS test shows that GARCH (1,1) is the best model in the short-run and competes with EGARCH (3,3) in the long-run. Therefore, using the MCS test, the GARCH (1,1) would be the relevant model for selection, while the error measures and cross-validation results suggest the choice of APARCH (3,1). As a result, GARCH (1,1) model is preferred, hence selected.

It is not very clear to understand which of the applied distribution assumptions would be the best for the fishing sector data among normal, student t- and skewed student t-distribution since, in a total of five models selected, two of them used normal distribution, and two applied student t-distribution while the fifth one applied skewed student t-distribution. However, in the total of 45 models run in the MCS test, majority of the models forecasted well with fat tails.

Observations from residuals, conditional mean and conditional variance plots

An analysis of the plot of annualized volatilities of the fisheries stocks over 10-year period (Figure 4.2) reflect that, generally, the volatility of the fisheries sector was much higher before the year 2004, although it had started reducing gradually at the beginning of the 21st century. From the year 2004 coming to 2016, the volatility of the fishing sector stocks staggered within relatively low levels for the majority of the stocks with the exception of AEE. This observation is in concord with the reviewed literature which discusses how mitigating strategies have been implemented over the past decade and half, and the achievements thereof. However, the volatility forecasts of the sector still reflect significantly high volatilities for the individual stocks, particularly for AEE, BRT and AVI. The test of stationarity of the data applied in constructing the VAR model resulted in a significant p-value (0.0005) for the Levin, Lin and Chu t-statistic which suggests no unit root in the data. Other unit root tests also show significant p-values, with Im, Pesaran and Shin W-statistic having a p-value approximately zero, ADF-Fisher Chi-square p-value of 0.0001 and PP-Fisher Chi-square also having a p-value of 0.0001. The Granger-causality test show that no causality effect of either direction exists between volatility of stocks and the four internal performance measures. The established Restricted-VAR model using 2 lags has an R-squared and Adjusted R-squared values of 0.472 and 0.360, respectively. In the volatility model, the significant variable is observed to be the second lag of volatility at 5% level of significance, while it has a negative effect on overall volatility. The MOS has only the first lag of EPS as a significant variable at 5% level. The EPS model also has one significant variable at 10% significance level, which is the second lag of FCF while the NW has second lag of EPS as the only significant factor also at 10% level.

The variance decomposition output of the VAR model shows that FCF and NW are the most significant factors contributing to the changes in volatility of the Western Cape fishing industry in the long-run. This is evidenced by the rise in their percentage contributions to volatility fluctuations with an increase in the horizon. The percentage contribution to volatility of FCF rises from 0.686% in year 2 to 25.901% in the 10^{th} year. The contribution of NW increases from 1.844% in year 2 to 11.403% in year 10.

The impulse responses of FCF and MOS positively impact on the volatility of the sector over the 10-year period, in general terms. However, NW and EPS have a negative effect on volatility. The MM estimation which takes care of the outlier effects in the model, indicate that all coefficients except for FCF are significant in the robust linear regression equation. The model has an R-squared of 0.385 and an Adjusted R-squared of 0.341.

Although there exist slight differences between results of the study and the evidence in the reviewed literature in terms of the extent to which identified factors individually affect volatility, the main common link is that volatility in Western Cape fishing sector tends to be high despite measures that have been implemented so far. Also, evidence of the study shows

that volatility is affected in the short-term mainly by the FCF and MOS. However, this finding contradicts to the results discovered by Hadassin (1986). Hadassin, in a study of the link between earnings and stock behaviour, realized a stronger relationship between earnings of firms and the share returns. However, Hadassin used only one fishing firm in the sample.
The AEE stock's volatility (shown in Figure 4.2), when considered in isolation, exhibits high fluctuations than the other firms. The daily volatility estimates of the other companies are also significantly high but the annualization in Figure 4.2 illusions some important information. As an example, the investigation of the conditional variances of the stocks shown in Appendix B (Figures B1 to B5), show the sharp jumps and falls experienced during the 2008-2009 financial crises period, but when the volatility estimates are annualized, the plot of the annualized figures only reflect a gentle rise in volatility for AVI and BRT during the period. Only AEE and OCE show a very sharp increase of volatility during that period from the plots in Figure 4.2. However, the behaviour of the annualized volatility plots for AVI and BRT could be reflecting a true story since these two companies heavily embarked on risk-mitigating strategies around the same period.

The sharp jumps and falls of fishing stocks is empirically evidenced. The reflection from some reports and articles, particularly for Irvin and Johnson (I&J) stock, AEE and BRT, attest to this investigation result. The AVI stock is singled-out in this illustration as a reflection on the negative impact the industry endures from the multiple risk factors. In a number of consecutive years, AVI returns go high by a huge margin while being punctuated by huge losses too as evidenced in years close to each other. For instance, the movements in the rand severely affected the AVI stock, both positively and negatively, in the years 2004, 2007, 2009, 2011 and 2015. Part of the argument to this effect is the fact that AVI performance also relies on exports to a large extent. As an example, an AVI report states that the Rand knocked over 8% off AVI earnings in the second half of the year 2004 and over 10% in the third quarter of 2009. According to report from Bloomberg (2006), AVI second-half net profit dropped 33% due to reduced fish catch. In the years 2011 and 2012, a 10% increase in the total allowable catch (TAC) for one of AVI's key fish products (hake), which followed a 1% increase in 2010, substantially boosted the company's returns and stock performance. The company management lamented performance shocks borne by sudden adjustments to the TAC for their major fish products, and expressed that additional TAC gives I&J an extra volume opportunity to boost business (ShareData, 2014). Also, AVI realized a 37.3% increase in net profit in fourth-quarter of 2015. There are numerous instances where risk factors in the sector impact performance sharply.

Differences in the behaviour of the trajectories for individual firm annual volatility plots indicate the different circumstances of the firms as well as the ability of the management of the firms in applying necessary strategies. Even though the patterns of the plots are varying, the general volatility of the sector has gradually eased over the past decade. A number of factors have been cited to explain the improvement in stability. Evidence suggests that various methods of reducing risk have been tried, with more of such efforts from the year 2002.

Although, apparently, the South African fishing firms have not yet begun implementing derivatives securities as in other financially-developed markets for hedging purpose, literature points out that acquisitions of firms in different sectors or firms vertically integrated for diversification purpose has become more and more common. For instance, Brimstone has made significant investments in the insurance firm, Lion of Africa, which has played a role in stabilising its business. Oceana acquired the US-based Daybrook Fisheries, which is a vertically-integrated business to its main activities, as part of the company's strategic changes to get new diversified incomes. SHH also acquired Mareterram Ltd (19.95%), an Australian Stock Exchange-listed company, a vertically integrated agribusiness.

Nevertheless, evidence exists that most Western Cape fishing firms have set foot in aquaculture and the intensity into the fish farming activity is growing each year for most of the sector players. This has been documented by a number of authors including the report from the Western Cape Government (2009) as a strategic approach to gaining stability as it has the potential of increasing their catch and market supply, and also reduces the uncertainty element with the wild marine populations estimation.

In an attempt to minimize uncertainty in quantifying fish stocks, there has been a significant improvement in marine population assessment procedures by some fishing firms, according to DAFF (2012). Western Cape sector companies have significantly improved their marine population assessment procedures and methodologies in addressing fish population uncertainty and management of fish stocks. Most of the firms now apply the latest bootstrapping statistical methodologies which have improved assessment estimations.

4.14. Conclusion

The analysis confirms relationship between volatility of the fishing sector and the internal performance measures and discovers high variability in the Western Cape fishing sector returns. In the Chapter 5 which follows, this paper gives conclusions of the study and outlines the recommendations for the managers of fisheries which are aimed at improving the returns and sustainability of the sector.

Chapter 5: Conclusion and recommendations

5.0. Introduction

In this section, a summary conclusion that is aligned to the key research objectives outlined in Chapter 1 (Section 1.3) is drawn. The conclusion is based on the findings of the study in comparison with the findings of previous and contemporary researchers. As indicated in Section 1.4, the conclusions and recommendations are directly intended for five main groups of stakeholders, namely; the managers of fisheries, investment analysts, portfolio managers, the investors and the academic community. Recommendations to the managers of fisheries are mainly intended to improve the risk-modelling methods as well as hedging and managing strategies. As for the investors, investment analysts and portfolio managers, the research will improve understanding of the risk-return profile of the fishing sector. This study attempts to lead to holistic understanding of the factors contributing to changes in fishing stock performance. It also demonstrates a quantitative risk-modelling approach which can be applied by fisheries managers. The study provides insight to potential investors and investment professionals on sector risks for improved stock evaluations and selection procedure. The findings and conclusions will also open up more space for further researches.

5.1. Key findings of the research study

5.1.1. Findings from the literature review

In this study, the literature investigated is assessed with the following interests; reviewing theory of volatility modelling in the context of fishing business, reviewing the theory of industry factors, industry performance, sector risk-modelling and management strategies. The common factors identified to be driving the volatility of fishing firms in the reviewed literature, in both international and local organisations include uncertainty with regard to fish stocks populations, changes in total allowable catch (TAC) limits, fluctuations in fuel prices, and natural hazards. Reviewed literature stress the significant variability in the performance of the fishing firms, which is expressed in most papers in terms of fluctuations in both production and profitability. No evidence is discovered in all the literature reviewed, on the use of contemporary risk or volatility modelling methods within the Western Cape fishing sector, for the purpose of evaluating performance or gaining insight on the nature of the sector returns and relationships among variables affecting returns volatility.

In some economies in which volatility models have been of use, there are varied beliefs in terms of what type of model best estimates the performance of the fisheries stocks. In general, evidence show that more researchers practically apply the univariate ARCH/ GARCH model type to assess equities due to the fact that factors affecting the variable of interest may be too many which may require estimation of too many parameters. Also, in some cases, it is difficult to ascertain all the factors involved. However, some researchers and practitioners find comfort in the multivariate GARCH (MGARCH) type due to its ability to capture co-movements effects among variables. The use of MGARCH models has also increasing been facilitated by the increased availability of financial data and increased computational abilities of computers. Many researches indicate that the choice of the best model-type depends to a large extent on the different circumstances of the financial asset being assessed. Wennstrom (2014) indicates that the decision on the appropriate model to apply is debatable and dependent upon the unique circumstances of the market being studied and to some extent on personal opinions and judgements.

In view of the literature findings, a double-pronged approach is preferred in this study, applying univariate GARCH to model the sector volatility while the VAR model is only used to study the variables relationships. Although most of the literature reviewed on volatility analysis in other economies suggests the application of univariate GARCH models, this study added to its analysis, the application of the VAR model in attempting to fully understand the volatility causes of the fishing sector, the impulse responses and variance decomposition. Thus, the VAR model is vital to investigate the extent to which volatility of fishing firms in Western Cape is influenced by its own lags (through univariate GARCH models) and also by the other commonly cited factors (MOS, EPS, FCF and NW). This approach is motivated in Caporin and McAleer (2011) in which the writers believe results will be more thorough and insightful on investigating the nature of the sector and variables of interest.

It is noted in the literature that fishing firms in Western Cape still experience high volatility although the fluctuation has gradually reduced in the recent years, particularly, from the year 2004. This is noted in the results of this study and others. The plots of actual series, conditional variances, annualized volatilities, the calculations of the forecasting performance evaluation measures, and the forecasts generally confirm high volatility for the sector. High volatility in the sector is also evidenced in numerous papers including Asche, Dahl and Steen (2015) and also in the Irvin and Johnson Report (2012). Also, fishing companies' quarterly, semi-annual and annual performance reports reflect on volatility. For instance, AVI's quarterly performances are an example to this note. Evidence exists that most of the Western Cape fishing companies have begun implementing some risk-mitigating measures and their individual stocks are becoming less jumpy from around the year 2002. According to Fin24 Report (2015) the decrease in volatility is primarily attributable to diversification strategies and better methods of assessments the fish stock as well as harvesting methods. The literature concurs with the findings of this study, as the volatility of the individual firms surveyed indicates a gradual drop over the past 15 years as shown in the volatility plots of four of the Western Cape fishing firms, BRT, OCE, AEE and AVI, found in Figure 4.2.

5.1.2. Findings of the study

In pursuit of the answer to the primary objective of the study, the study established five optimal GARCH models for estimating volatility of the individual firms under study which are EGARCH (6,5) for BRT stock, GARCH (1,1) for OCE, EGARCH (2,1) for AEE, EGARCH (2,3) for AVI and GARCH (1,1) for SHH. Forecasts of BRT, OCE, AEE and AVI 120-day future volatilities are estimated using the selected optimal models. The study establishes the VAR model for the firms under study which helped in indicating some important insight about relationships of factors with volatility, which include the significance of internal performance factors in influencing volatility, Granger-causality among the variables, variance decomposition and impulse responses. The methodology followed in this study is consistent with the work of Alberg et al (2008) and Wang and Wu (2012). Alberg investigated some stocks on the Tel Aviv Stock Exchange (TASE) while Wang and Wu forecasted energy market volatility in China. The results obtained by Alberg (2008) show that the asymmetric GARCH models with fat-tailed densities improved overall estimation for measuring conditional variance. Alberg et al (2008) discovered that the EGARCH model, using a skewed Student-t distribution, is the most successful model for forecasting the TASE stocks. Wang et al (2012) also apply various GARCH models to compare performance of symmetric against the asymmetric GARCH models. Wang and Wu (2012) applied the VAR model to obtain more insight on the interactions of the energy sector variables. According to the results of Wang and Wu (2012), the univariate models, allowing for asymmetric effects, display the greatest accuracy. However, Wang and Wu subsequently stressed the value of multivariate models in discovering and quantifying impact of factors affecting stocks. This helped Wang and Wu to identify the relevant hedging strategies for the energy market based on the additional insight provided by multivariate models, and also stressed the implications for market participants. The findings of Alberg et al (2008) and Wang and Wu (2012) are consistent with the results of this study as the asymmetric EGARCH model assuming Student t-distribution dominated the results with the lowest forecasting performance evaluation measures, based on MSE, MAE, MedSE, RMSE and TIC, as well as the superiority predictive ability tests. Three firms in five (60%) in this study are best modelled by the EGARCH model, according to the results. The other two firms are modelled better by GARCH (1,1) model.

Therefore, this study's results are in two forms, that is, the established optimal models (Table 4.7) and the forecast estimates from the models, which have graphical illustrations shown in Appendix C. The estimated forecasts of volatility from the univariate GARCH models show that, in general, the fishing sector's short-term unconditional variance is expected to drop to a lower long-term covariance after a relatively longer period. The VAR model provides some complementary dimensions to the analysis which are not obtainable from the univariate GARCH.

The EGARCH model under student t and student skewed t-distribution, outperforms other GARCH types applied in the study. The other model that featured in the estimation of volatility of the fishing sector are GARCH (1,1) assuming normal distribution. In the VAR model, it is realised that, three variables (VOL lag, FCF and NW) are more significant in the long-run forecast of volatility for the fishing stocks, with pre-tax income (MOS) having less effect, and the EPS having relatively more influence on VOL in the short-term than in the long-run.

The research also discovers that the most volatile stocks are those firms not effectively implementing the risk-mitigating strategies, such as, diversification (vertical and horizontal integration), hedging and aquaculture.

5.1.3. Conclusions

In line with the first objective of this study, the study established the best GARCH models for forecasting volatility of each of the JSE-listed Western Cape fishing companies. Even though there is a gradual reduction, volatility of the firms under investigation in this study is still relatively high for investors. The next section of this study covers the conclusions and suggested recommendations based on findings.

5.2. Recommendations

The first step in the process of crafting and outlining solution strategies or recommendations to the fishing sector requires taking note of the fact that some factors are, theoretically, less controlled by or out of control of the fisheries managers. Two categories of risk factors exist to the problem, that is, systematic and idiosyncratic risk factors. Idiosyncratic risk can be substantially mitigated using relevant diversification, while hedging is vital against systematic risks and other risks to do with disasters. Theory suggests that there are relatively more solution strategies mainly to the firms' internal compared to its external factors.

Several internal and external factors for fishing business are evidenced in different papers. However, this research outlines, as recommendations, suggestions of solution strategies mainly to the key issues (key factors) bedevilling the Western Cape fishing sector. The study firstly discusses the strategies which relate to the internal factors of the fishing businesses and later extend the discussion to the factors which emanate from outside the firm.

There are a number of solution strategies that the fishing firms may implement to mitigate the impact of internal factors. To start with, fisheries managers need to have a holistic understanding of the nature of their business and the factors involved. Fishing companies need to keep updating and calibrating their systems and methods for assessing fish stocks since uncertainty in fish populations remains a big challenge. The companies which are still using old methods of assessing fish stocks need to adopt the new systems, methods and procedures for assessing fish stocks to improve business performance. As advocated in Kirkwood (2003) and Edwards, Hillary, Levontin, Blanchard and Lorenzen (2012), the companies need to establish rational economic harvest policy to safeguard against stock collapse. They also need to establish an adaptive annual harvest quota and minimum stock level where harvest is curtailed.

The Western Cape fishing sector should implement quantitative risk models in evaluating the business risk and relationships with the associated risk factors as it will help to identify relevant area of concentration of effort and most appropriate hedging strategies, hence improve business performance results. Diversification, utilizing vertical and horizontal integration strategies, can also benefit the sector if effectively implemented. Merger partners can be carefully chosen to place business in the best position to exploit the benefits of scale economies, and creation of operating leverage, in addition to diversification advantages. However, in exercising this strategy, care should be taken to ensure that there is fit of objectives, culture and values between the merged elements to ensure efficient operation of the resultant merged firm.

As evidenced in Norway, future derivative contracts together with other useful hedging securities suits the fishing sector and can be effectively implemented to hedge the position of the business against various uncertainties. The use of hedging may not only be against ecological volatility and market price risk, but may also be used to protect from uncertainty in many other variables of fishing business, such as fuel price oscillations. Since commercial fishing activities consume huge quantities of fuel, a small change in fuel price largely affects business performance in positive or negative direction, depending on the direction of motion of fuel price. Therefore, it is necessary to hedge against unfavourable movements in the price of this fisheries production input.

It is also of paramount importance that the fishing companies hire skilled fisheries managers. The companies must further establish solution strategies to the problem of scarcity of fisheries management skills, through succession planning and other relevant human resources practices. This is suggested since one of the key factors stated in some articles is shortage of the vital skills in the sector.

Nevertheless, the operations of fishing ships are stated to be associated with many accidents. Increased number of accidents impedes production. This has been cited in Kirkwood (2003) and other papers as one of the causes of shocks to the fishing stocks. Therefore, the safety of the seagoing workers and fishing ships should be addressed accordingly. The fishing companies need to establish systematic ways of identifying main causes of the accidents and take major preventive measures to improve company performance.

There are also measures that the firms could resort to in order to curb or hedge the negative effect of the external factors. This includes measures to hedge against fish stock collapse, changes in Total Allowable Catch (TAC) restrictions, natural hazards, exchange rate and fuel price changes. It should be noted that most of the externally-borne risks mainly require hedging as a solution. The discussion of the factors is not exhaustive because of the multiple risk factors of the sector, therefore the solution strategies recommended should serve as a guide particularly for the key issues bedevilling the fishing sector. If GARCH models can be used to identify the factors that contribute most to volatility jumps then the firms will be able to focus on strategies for hedging the identified risk factors.

Where fish stock collapse is the main risk, rational economic harvest policy safeguards against stock collapse by establishing an adaptive annual harvest quota and minimum stock level where harvest is curtailed. This is similar to biological benchmarks developed in the technical fisheries literature (Kirkwood, 2003). The opening of fish-farming activities (aquaculture) with rational harvest policies can stabilize the fish production levels for the companies hence reduce volatility due to variations in production levels. The next section (Section 5.4) outlines the limitations of this study.

5.3. Limitations of the research

Care should be taken in implementing the results of this study due to two main reasons. Firstly, the data applied in obtaining VAR model is limited to 15 observations (for 15 years) which may result in less reliable results. This is the case due to the fact that the data pertaining to the four internal performance variables (EPS, MOS, NW and FCF) is all annual. Secondly, the study used only five firms on the JSE. The sample applied may not fully capture the distributional properties of the fishing sector population of companies. For instance, in determining the best GARCH model type for modelling the fishing stocks, three firms are more accurately measured by EGARCH, and the other two by GARCH (1,1). The small sample size may be a major limitation on passing of conclusions about the distribution of best model types for modelling fishing sector.

5.4. Areas for further research

This study gives a reflection of the nature of volatility of the fishing industry based on the stock price series as well as the series of their internal performance indicators, EPS, MOS, FCF and NW. However, there are other aspects of the volatility analysis which when exploited could be both statistically and intuitively vital towards improving understanding of the fishing sector performance. For example, the research does not fully embrace the qualitative factors involved in running fisheries. Further investigation into such factors would enrich the results of this study. Also, EPS, MOS, FCF and NW are the key factors referred to in many researches and this study. However, a further analysis of the relationships of other sector factors, particularly, the external, cited in some literature such as TAE and fuel price oscillations, would also improve the results.

Nevertheless, some of the suggested methods or strategies for curbing fishing business volatility have been implemented primarily in more technologically and financially developed markets within Europe, America and Australian continents. An investigation of the feasibility of such methods within the Western Cape context is imperative and would enrich the findings.

Furthermore, since the fishing industry is a dynamic business with constantly improving fish stock assessment methods, further studies on effects of subsequent introduction of new technology for fish harvesting (particularly, deep-sea fishing) and new fish farming methods is key. Also, further researches on the extent to which some risk factors are becoming manageable and studies on any cost-saving and production-improving industry innovations will give more insights and help redirect the research results. Further researches on volatility forecasting incorporating updated industry systems and any changes on the fisheries market will help refine and calibrate the research model to improve robustness of research results.

5.5. Conclusion

It is vital for the managers of fishing firms to understand holistically the fishing business and its risk factors, as a starting point, to establish appropriate measures for improved management. The process incorporates the application of appropriate volatility modelling approaches which serve to disillusion the circumstances to fishing business. Moreover, a constant update of the new and emerging fisheries risk management and hedging strategies should be maintained in order to ensure that the profitability and sustainability of fishing business is enhanced. This research opens opportunity for further research to improve the management of fishing business.

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Appendices

Appendix A: MCS Test Results

AEE MCS test results:

Table A1: AEE Ranking of the models for the 30-day forecast:

Superior model set created:							
Model	**Rank_M**	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model30EG_N	3	-1.26696866	1	1	0.000000	1	1.364959
model30EG_T	1	-1.26736451	1	2	0.000000	1	1.364959
model30EG_st	2	-1.26702663	1	3	0.000000	1	1.364959
model30GJ_N	9	1.1776042	1	9	1.631359	0.0524	1.369991
model30GJ_T	7	1.17710697	1	7	1.631284	0.0592	1.369991
model30GJ_st	8	1.17737171	1	8	1.631284	0.0592	1.369991
model30AP_N	5	0.08991227	1	4	0.905083	1	1.367752
model30AP_T	4	0.08989512	1	5	0.905083	1	1.367752
model30AP_st	6	0.08992419	1	6	0.905176	1	1.367752
p-value	:						
[1]	1						

Table A2: AEE Ranking of the models for the 60-day forecast:

Superior model set created:							
Model	**Rank_M**	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model60G_N	12	0.9915818	1	12	1.686644	0.427	1.025031
model60G_T	10	0.9883629	1	14	1.6901272	0.427	1.025031
model60G_st	14	0.9923847	1	11	1.6860475	0.427	1.025031
model60EG_N	8	0.316631	1	9	1.2376600	1	1.024846
model60EG_T	9	0.3173594	1	7	1.2362186	1	1.024846
model60EG_st	7	0.3165347	1	8	1.2371627	1	1.024846
model60GJ_N	2	-1.4879926	1	1	0.0000000	1	1.024355
model60GJ_T	1	-1.4891991	1	2	0.0000000	1	1.024355
model60GJ_st	3	-1.4858937	1	3	0.0000000	1	1.024355
model60AP_N	5	-0.8214821	1	6	0.4568137	1	1.024536
model60AP_T	4	-0.8225945	1	4	0.4564337	1	1.024536
model60AP_st	6	-0.8210817	1	5	0.4566413	1	1.024536
model60GM_N	13	0.9915818	1	10	1.6859579	0.427	1.025031
model60GM_T	11	0.9883629	1	15	1.6901272	0.427	1.025031
model60GM_st	15	0.9923847	1	13	1.6883568	0.427	1.025031
p-value	:						
[1]	1						

Table A3: AEE Ranking of the models for the 90-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model90EG_N	8	1.1128244	1	9	1.617408	0.7654	1.340714
model90EG_T	9	1.1133381	1	7	1.616985	0.7654	1.340714
model90EG_st	7	1.1127364	1	8	1.616985	0.7654	1.340714
model90GJ_N	1	-1.3122938	1	1	0.000000	1	1.339932
model90GJ_T	3	-1.3115630	1	2	0.000000	1	1.339932
model90GJ_st	2	-1.3119034	1	3	0.000000	1	1.339932
model90AP_N	6	0.1987214	1	4	1.008172	1	1.340419
model90AP_T	4	0.1986835	1	5	1.008172	1	1.340419
model90AP_st	5	0.1986842	1	6	1.008172	1	1.340419
p-value :							
[1]	1						

Table A4: AEE Ranking of the models for the 120-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model120EG_N	14	1.0140532	1	12	1.848774	0.6106	7.599081
model120EG_T	10	1.0117830	1	11	1.844642	0.6306	7.599081
model120EG_st	12	1.0133004	1	15	1.849905	0.6056	7.599081
model120EG_N_1	3	-1.6869125	1	1	0.000000	1	7.593870
model120EG_T_1	1	-1.6950849	1	2	0.000000	1	7.593870
model120EG_st_1	2	-1.6913814	1	3	0.000000	1	7.593870
model120GJ_N	6	-0.1909214	1	5	1.030188	1	7.596764
model120GJ_T	4	-0.1911696	1	6	1.030303	1	7.596764
model120GJ_st	5	-0.1910846	1	4	1.027594	1	7.596764
model120AP_N	9	-0.1412166	1	8	1.064293	1	7.596860
model120AP_T	7	-0.1413937	1	9	1.064441	1	7.596860
model120AP_st	8	-0.1413330	1	7	1.061586	1	7.596860
model120GM_N	15	1.0140532	1	13	1.848774	0.6160	7.599081
model120GM_T	11	1.0117830	1	14	1.849518	0.6106	7.599081
model120GM_st	13	1.0133004	1	10	1.843926	1	7.599081
p-value :							
[1]	1						

AVI MCS test results:

Table A5: AVI Ranking of the models for the 30-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model30G_N	8	-0.09752117	1	8	1.136336	1	10.41001
model30G_T	6	-0.09753397	1	5	1.132130	1	10.41001
model30G_st	4	-0.09757873	1	6	1.132262	1	10.41001
model30EG_N	2	-1.75423929	1	1	0.000000	1	10.39040
model30EG_T	3	-1.75371384	1	2	0.000000	1	10.39040
model30EG_st	1	-1.75469700	1	3	0.000000	1	10.39040
model30GJ_N	14	1.00743295	1	15	1.894611	0.6708	10.42309
model30GJ_T	13	1.00724404	1	14	1.893800	0.7072	10.42309
model30GJ_st	15	1.00781204	1	13	1.886543	0.826	10.42309
model30AP_N	11	0.94207721	1	12	1.849789	1	10.42232
model30AP_T	10	0.94190019	1	11	1.848994	1	10.42232
model30AP_st	12	0.94242950	1	10	1.841908	1	10.42232
model30GM_N	9	-0.09752117	1	9	1.136336	1	10.41001
model30GM_T	7	-0.09753397	1	7	1.135849	1	10.41001
model30GM_st	5	-0.09757873	1	4	1.131554	1	10.41001
p-value	:						
[1]	1						

Table A6: AVI Ranking of the models for the 60-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model60G_N	10	1.0126138	1	13	1.848037	0.6068	7.599081
model60G_T	14	1.0137069	1	10	1.839697	0.6246	7.599081
model60G_st	12	1.0133662	1	11	1.845249	0.6068	7.599081
model60EG_N	1	-1.6905759	1	1	0.000000	1	7.593870
model60EG_T	3	-1.6900468	1	2	0.000000	1	7.593870
model60EG_st	2	-1.6905428	1	3	0.000000	1	7.593870
model60GJ_N	6	-0.1909667	1	5	1.029999	1	7.596764
model60GJ_T	5	-0.1910655	1	6	1.030637	1	7.596764
model60GJ_st	4	-0.1910943	1	4	1.028122	1	7.596764
model60AP_N	9	-0.1412418	1	8	1.064153	1	7.596860
model60AP_T	8	-0.1413201	1	9	1.064777	1	7.596860
model60AP_st	7	-0.1413439	1	7	1.062172	1	7.596860
model60GM_N	11	1.0126138	1	14	1.848037	0.6068	7.599081
model60GM_T	15	1.0137069	1	15	1.849976	0.6016	7.599081
model60GM_st	13	1.0133662	1	12	1.845249	0.6180	7.599081
p-value	:						
[1]	1						

Table A7: AVI Ranking of the models for the 90-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model90G_N	12	1.1412487	0.9994	14	1.7420660	0.552	5.977682
model90G_T	10	1.1411693	0.9994	12	1.7394849	0.552	5.977682
model90G_st	14	1.1429498	0.9994	13	1.7410073	0.552	5.977682
model90EG_N	2	-1.4089363	1	1	0.0000000	1	5.972205
model90EG_T	1	-1.4108684	1	2	0.0000000	1	5.972205
model90EG_st	3	-1.4071186	1	3	0.0000000	1	5.972205
model90GJ_N	6	-0.4549288	1	6	0.6557476	1	5.974260
model90GJ_T	4	-0.4552346	1	5	0.6548345	1	5.974260
model90GJ_st	5	-0.4549779	1	4	0.6544170	1	5.974260
model90AP_N	9	-0.4170083	1	9	0.6817484	1	5.974341
model90AP_T	7	-0.4172807	1	8	0.6807725	1	5.974341
model90AP_st	8	-0.4170239	1	7	0.6803612	1	5.974341
model90GM_N	13	1.1412487	0.9994	15	1.7420660	0.552	5.977682
model90GM_T	11	1.1411693	0.9994	11	1.7384411	0.552	5.977682
model90GM_st	15	1.1429498	0.9994	10	1.7366926	0.559	5.977682
p-value	:						
[1]	0.9994						

Table A8: AVI Ranking of the models for the 120-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model120G_N	6	-0.1584606	1	7	0.5173506	1	5.591653
model120G_T	4	-0.1605751	1	5	0.5147190	1	5.591653
model120G_st	8	-0.1563389	1	4	0.5135267	1	5.591653
model120GJ_N	2	-1.0052516	1	1	0.0000000	1	5.591524
model120GJ_T	3	-0.9935313	1	2	0.0000000	1	5.591524
model120GJ_st	1	-1.0191221	1	3	0.0000000	1	5.591524
model120AP_N	11	1.3150827	0.2794	12	1.8807803	0.2036	5.591878
model120AP_T	10	1.2988352	0.2916	10	1.8779608	0.2134	5.591878
model120AP_st	12	1.3328868	0.2698	11	1.8791124	0.2098	5.591878
model120GM_N	7	-0.1584606	1	8	0.5173506	1	5.591653
model120GM_T	5	-0.1605751	1	6	0.5159484	1	5.591653
model120GM_st	9	-0.1563389	1	9	0.5196135	1	5.591653
p-value	:						
[1]	0.2698						

OCE MCS test results:

Table A9: OCE Ranking of the models for the 30-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model30G_N	11	0.9990438	0.6586	11	1.351590	0.659	5.797134
model30G_T	7	0.9982580	0.6638	9	1.351355	0.659	5.797134
model30G_st	9	0.9990089	0.6586	8	1.351157	0.659	5.797134
model30GJ_N	5	-0.9981755	1	1	0.000000	1	5.796288
model30GJ_T	1	-0.9989611	1	2	0.000000	1	5.796288
model30GJ_st	3	-0.9982103	1	3	0.000000	1	5.796288
model30AP_N	6	-0.9981755	1	4	0.000000	1	5.796288
model30AP_T	2	-0.9989611	1	5	0.000000	1	5.796288
model30AP_st	4	-0.9982103	1	6	0.000000	1	5.796288
model30GM_N	12	0.9990438	0.6586	12	1.351590	0.659	5.797134
model30GM_T	8	0.9982580	0.6638	10	1.351355	0.659	5.797134
model30GM_st	10	0.9990089	0.6586	7	1.350994	0.659	5.797134
p-value	:						
[1]	0.6586						

Table A10: OCE Ranking of the models for the 60-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model60G_N	1	-1.1703113	1	1	0.000000	1	6.527481
model60G_T	3	-1.1698873	1	2	0.000000	1	6.527481
model60G_st	5	-1.1679971	1	3	0.000000	1	6.527481
model60EG_N	7	0.2410544	1	9	0.964848	1	6.529692
model60EG_T	8	0.2411139	1	8	0.964797	1	6.529692
model60EG_st	9	0.2413998	1	7	0.964527	1	6.529692
model60GJ_N	10	1.0491136	1	12	1.517169	0.3556	6.530958
model60GJ_T	12	1.0493011	1	14	1.517493	0.3556	6.530958
model60GJ_st	14	1.0498952	1	10	1.517101	0.3624	6.530958
model60AP_N	11	1.0491136	1	13	1.517169	0.3624	6.530958
model60AP_T	13	1.0493011	1	15	1.517493	0.3556	6.530958
model60AP_st	15	1.0498952	1	11	1.517101	0.3808	6.530958
model60GM_N	2	-1.1703113	1	4	0.000000	1	6.527481
model60GM_T	4	-1.1698873	1	5	0.000000	1	6.527481
model60GM_st	6	-1.1679971	1	6	0.000000	1	6.527481
p-value	:						
[1]	1						

Table A11: OCE Ranking of the models for the 90-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model90G_N	2	-0.6526541	1	1	0.000000	1	6.390198
model90G_T	5	-0.6492278	1	2	0.000000	1	6.390198
model90G_st	3	-0.6512267	1	3	0.000000	1	6.390198
model90EG_N	9	1.0822270	0.1416	7	1.073175	0.4888	6.390397
model90EG_T	8	1.0810370	0.1424	8	1.076176	0.4888	6.390397
model90EG_st	7	1.0735466	0.147	9	1.076176	0.4888	6.390397
model90GM_N	4	-0.6507412	1	4	0.000000	1	6.390198
model90GM_T	1	-0.6540431	1	5	0.000000	1	6.390198
model90GM_st	6	-0.6483537	1	6	0.000000	1	6.390198
p-value	:						
[1]	0.1416						

Table A12: OCE Ranking of the models for the 120-day forecast:

Superior model set created:							
	Rank_M	**v_M**	**MCS_M**	**Rank_R**	**v_R**	**MCS_R**	**Loss**
model120G_N	4	-0.4116567	1	5	0.7005416	1	5.265575
model120G_T	8	-0.4111884	1	8	0.7012520	1	5.265575
model120G_st	6	-0.4113546	1	4	0.6991609	1	5.265575
model120EG_N	3	-1.4367999	1	1	0.0000000	1	5.264753
model120EG_T	1	-1.4384349	1	2	0.0000000	1	5.264753
model120EG_st	2	-1.4384258	1	3	0.0000000	1	5.264753
model120GJ_N	12	1.1332159	0.9996	12	1.7635932	0.1276	5.266811
model120GJ_T	10	1.1331420	0.9996	14	1.7647476	0.1202	5.266811
model120GJ_st	14	1.1338578	0.9996	10	1.7592636	0.1296	5.266811
model120AP_N	13	1.1332159	0.9996	13	1.7635932	0.1276	5.266811
model120AP_T	11	1.1331420	0.9996	15	1.7647476	0.1202	5.266811
model120AP_st	15	1.1338578	0.9996	11	1.7592636	0.1296	5.266811
model120GM_N	5	-0.4116567	1	6	0.7005416	1	5.265575
model120GM_T	9	-0.4111884	1	9	0.7030457	1	5.265575
model120GM_st	7	-0.4113546	1	7	0.7009522	1	5.265575
p-value	:						
[1]	0.9996						

Appendix B: Squared residuals, conditional mean and conditional variance plot

Figure B1: OCE squared residuals, conditional mean and conditional variance plot

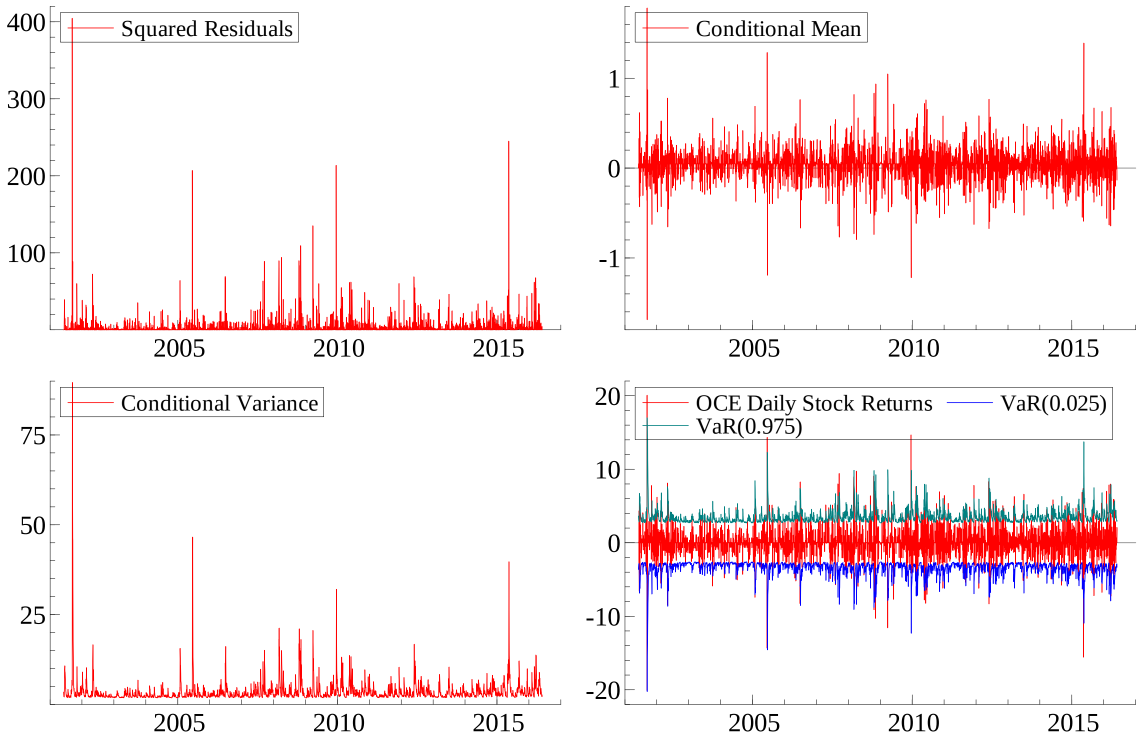


Figure B2: BRT squared residuals, conditional mean and conditional variance plot

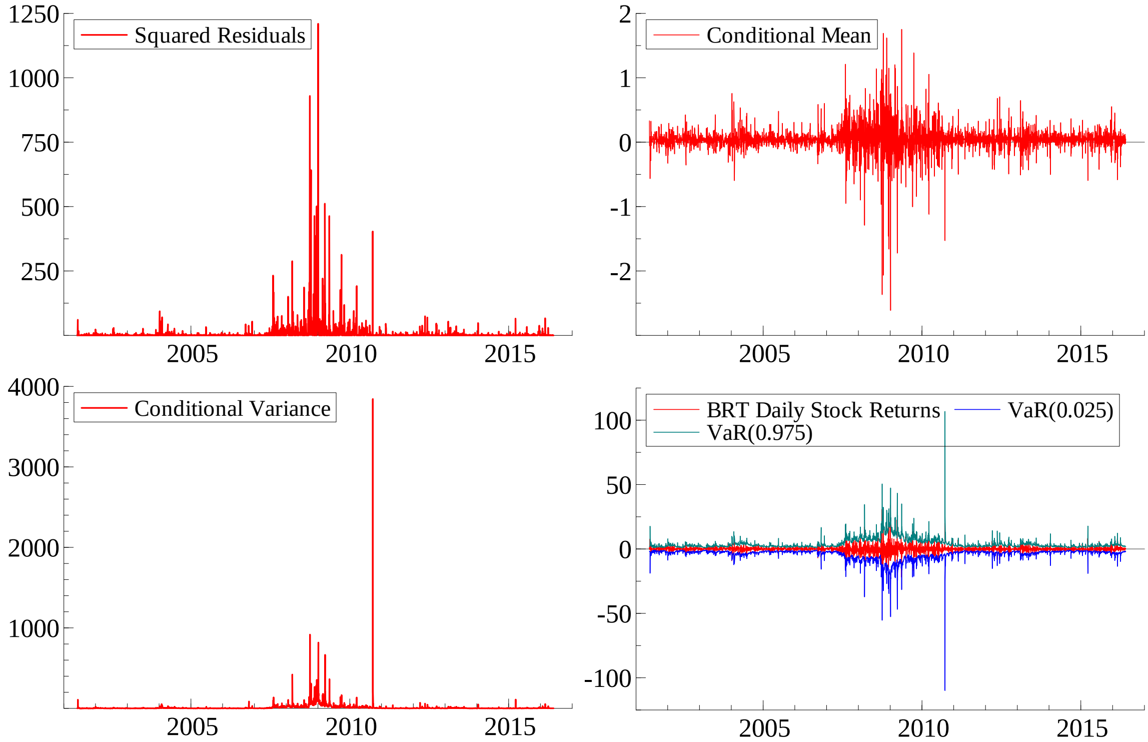


Figure B3: AEE squared residuals, conditional mean and conditional variance plot

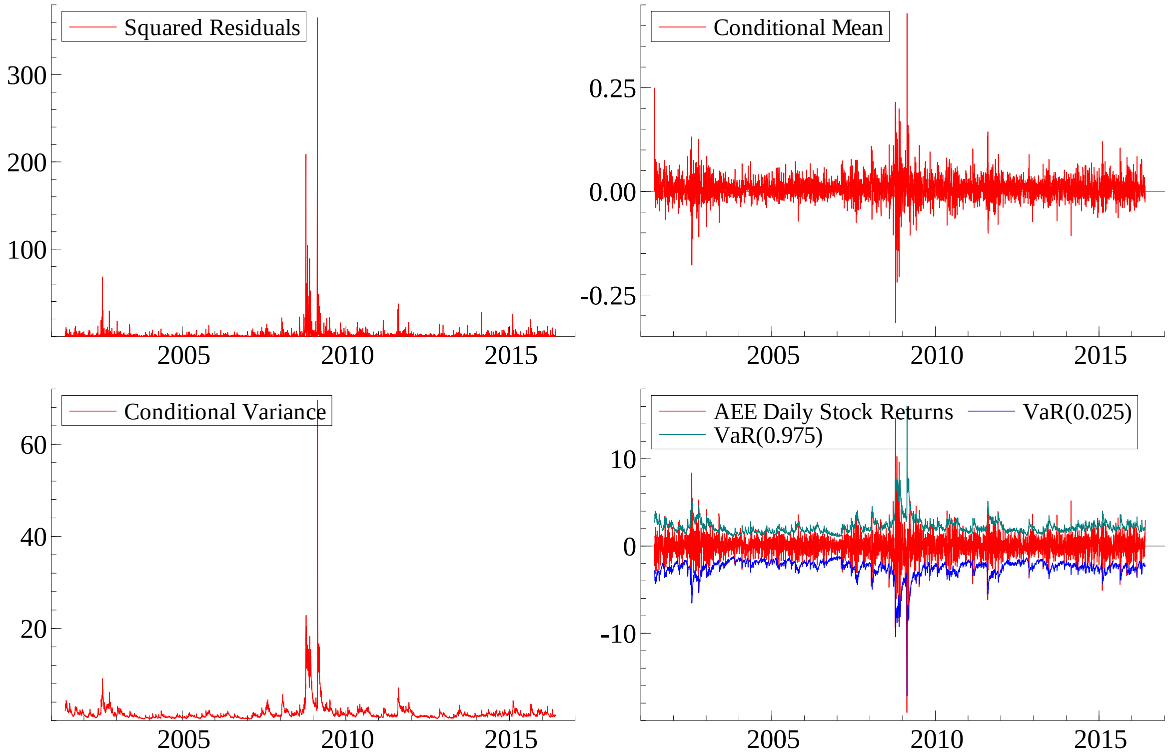


Figure B4: AVI squared residuals, conditional mean and conditional variance plot

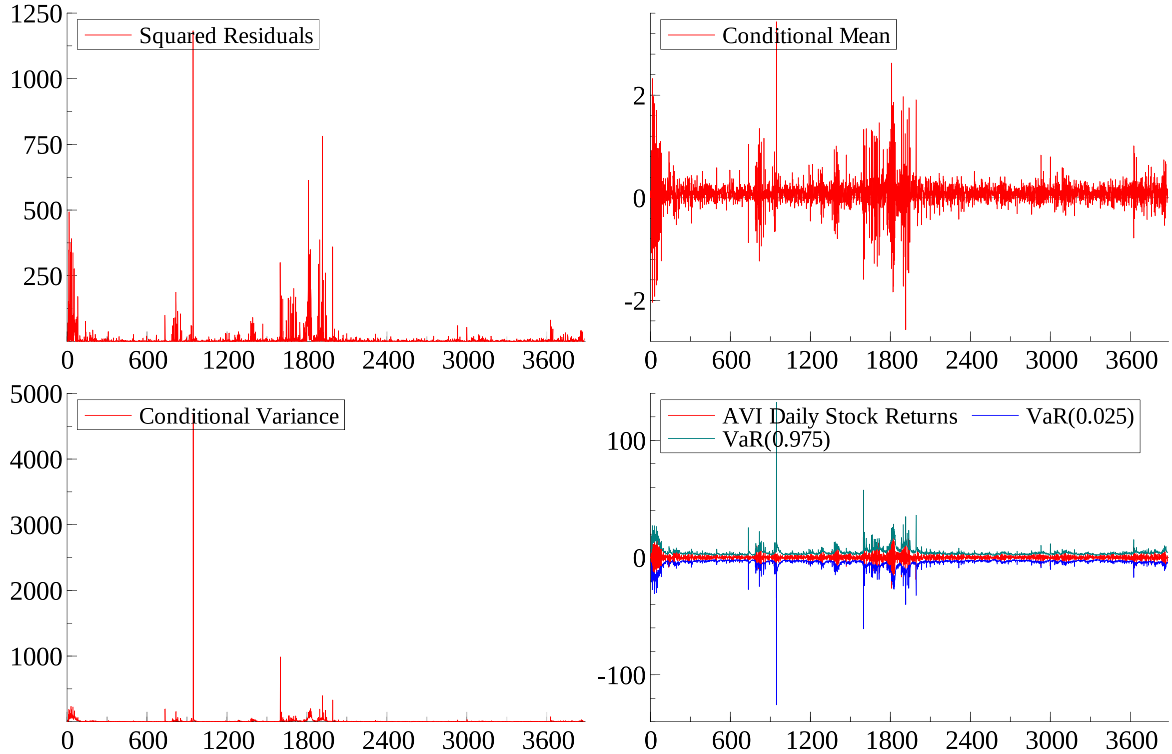
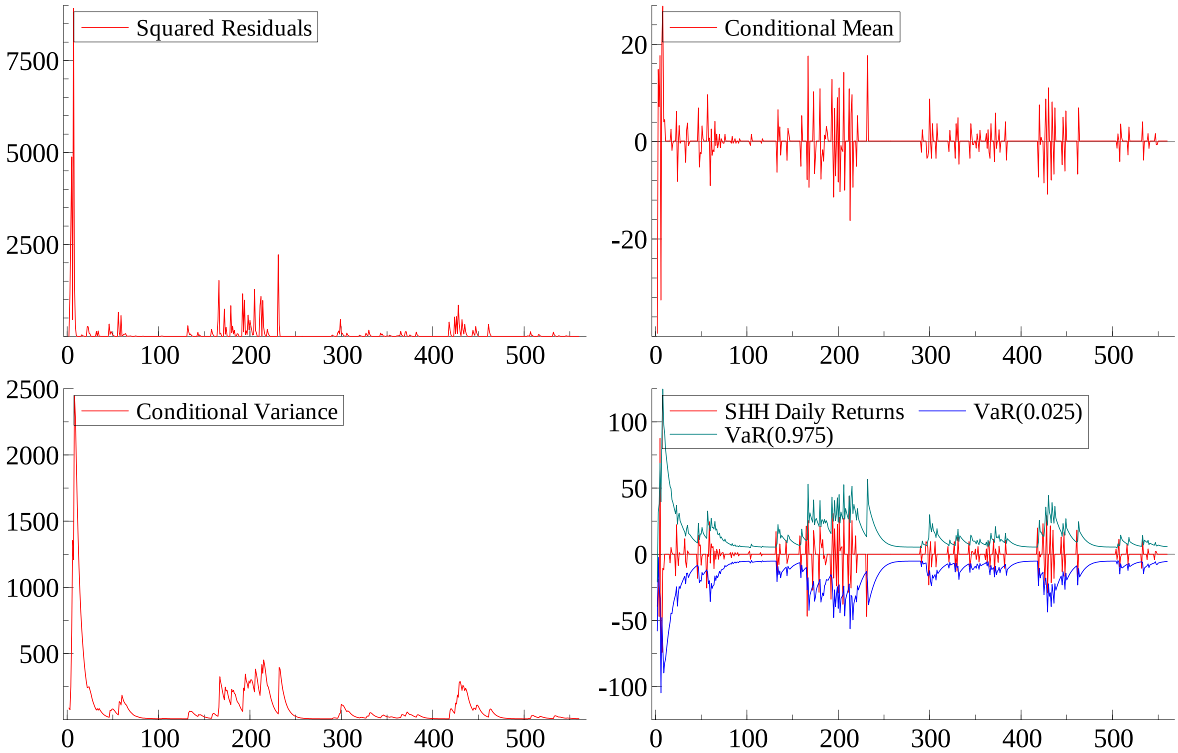


Figure B5: SHH squared residuals, conditional mean and conditional variance plot



Appendix C: Volatility forecasts

Figure C1: BRT Volatility forecasts

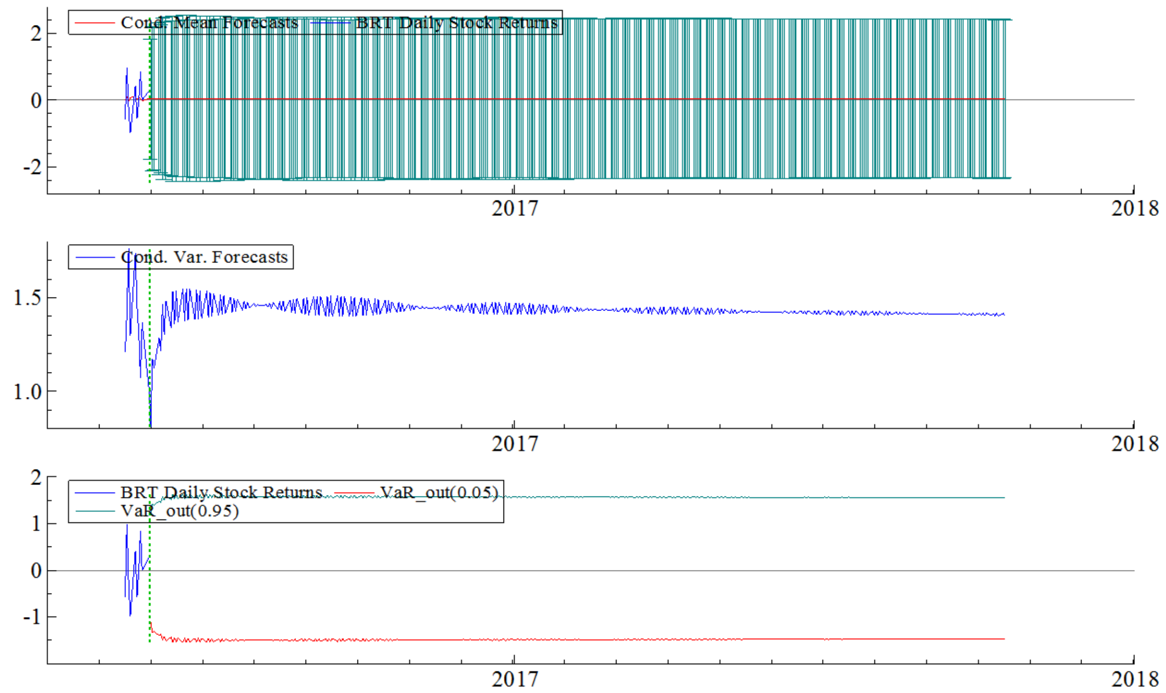


Figure C2: OCE Volatility forecasts

Figure C3: AEE Volatility forecasts

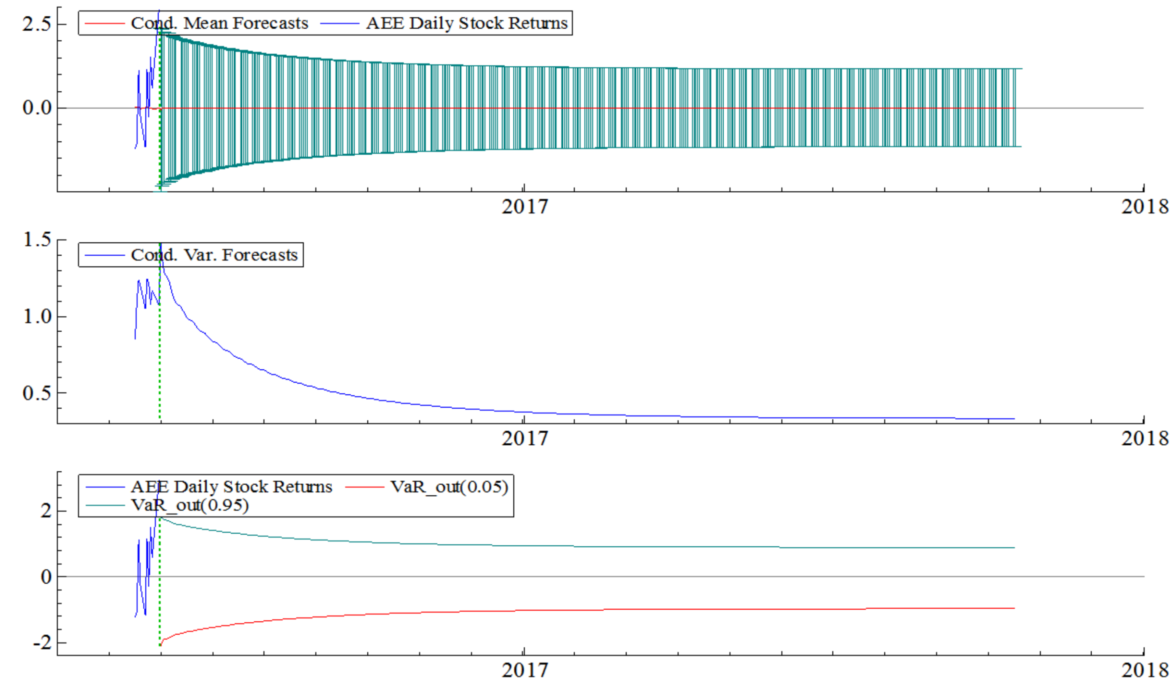
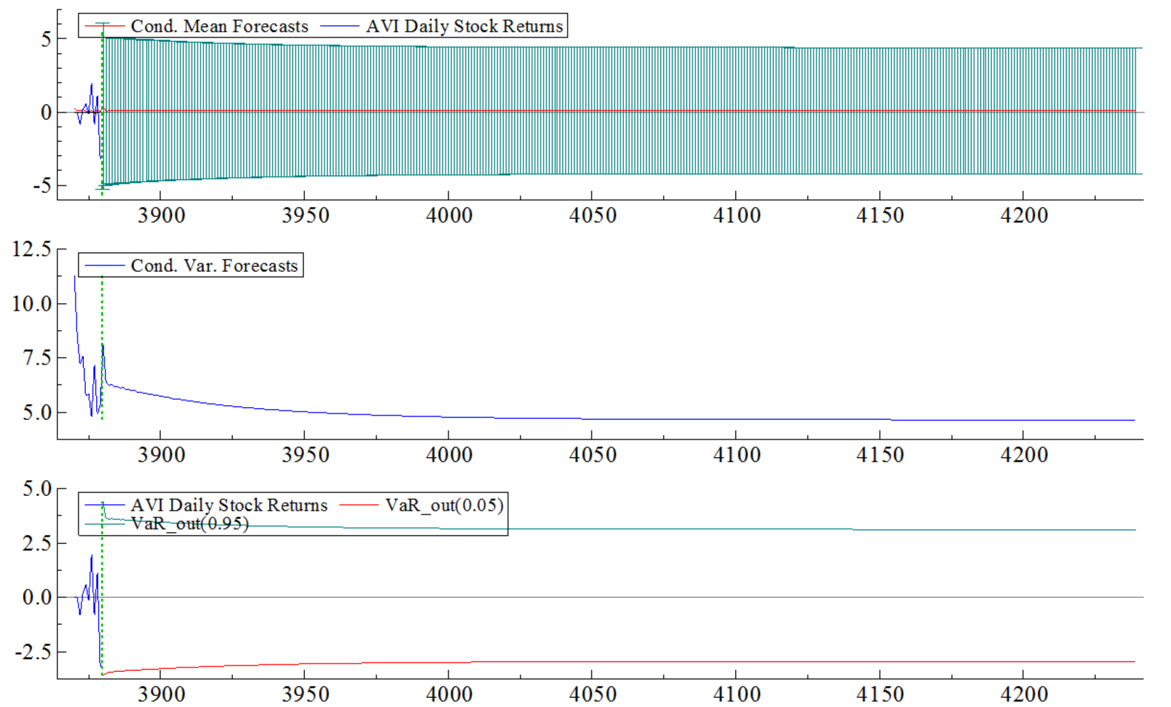


Figure C4: AVI Volatility forecasts



Appendix D: VAR Model Unit Root Test and Pairwise Granger Causality Test

Table D1: Group unit root test: Summary

Series: VOL, NW, FCF, EPS, MOS

Sample: 1 60

Exogenous variables: Individual effects

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0

Newey-West automatic bandwidth selection and Bartlett kernel

Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.27198	0.0005	4	60
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.16902	0.0000	4	60
ADF - Fisher Chi-square	35.6407	0.0001	4	60
PP - Fisher Chi-square	35.9835	0.0001	4	60

Table D2: Pairwise Granger Causality Test Results

Sample: 1 60 Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
NW does not Granger Cause VOL	58	1.63513	0.2046
VOL does not Granger Cause NW		1.82798	0.1007
FCF does not Granger Cause VOL	58	1.26167	0.2915
VOL does not Granger Cause FCF		1.12729	0.3316
EPS does not Granger Cause VOL	58	0.99665	0.3759
VOL does not Granger Cause EPS		0.76240	0.4716
MOS does not Granger Cause VOL	58	1.34079	0.2704
VOL does not Granger Cause MOS		0.48712	0.6171
FCF does not Granger Cause NW	58	1.97455	0.1489
NW does not Granger Cause FCF		1.02615	0.3654
EPS does not Granger Cause NW	58	1.29213	0.2832
NW does not Granger Cause EPS		2.46704	0.0945
MOS does not Granger Cause NW	58	1.74283	0.1849
NW does not Granger Cause MOS		2.00793	0.1444
EPS does not Granger Cause FCF	58	0.13817	0.8713
FCF does not Granger Cause EPS		0.27512	0.7606
MOS does not Granger Cause FCF	58	1.03959	0.3607
FCF does not Granger Cause MOS		2.00882	0.1442
MOS does not Granger Cause EPS	58	0.07163	0.9310
EPS does not Granger Cause MOS		0.16871	0.8452