COMPARISON OF VALUE AT RISK MODELS AND EXPECTED SHORTFALL MODELS FOR SELECTED MINERAL COMMODITIES

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DECLARATION

I declare that this research report is my own, unaided work. It is being submitted to the Degree of Master of Science to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other University.

Signed:

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Katlego Masilu Letsoalo

This____________ day of _________________ year_______________

ABSTRACT

Risk management is a critical component of modern-day finance with the banking sector having led the developments over the years. Following the impacts of the Global Financial Crisis of mid-2008 on various markets, investors are more concerned with their overall risk exposure including mining companies. Literature presents Value at Risk (VaR) and Expected Shortfall (ES) methods as the most common mechanism used to determine risk exposure. These methods have not been applied extensively in the mining sector despite their popularity in the finance sector.

This research study explores the theoretical concept of VaR as a method of risk measurement including the computational considerations and some of the drawbacks of these models. Several studies criticise the ability of VaR to capture risk in a portfolio particularly during a period of risk. Given the drawbacks of VaR, ES is discussed as an alternative method including a comparison of key parameters between the two methods.

This research study investigated the most optimal risk exposure evaluation methods for mineral commodities with a focus on coal and gold mining companies listed in South African given the commodities risk exposures and the available Mineral Resources. To apply the risk measurement methods a less volatile period was chosen as a time horizon, data from 2013 to 2019. The study calculated VaR using parametric model through the variance–covariance method, semi-parametric model through Monte Carlo Simulation and non-parametric models using Historical simulation methods. The alternative risk measure was calculated using ES.

The outcomes of the VaR models are compared to the ES model to determine the risk measure that captures the possible losses with the highest degree of confidence. The accuracy of the models was tested through a process of backtesting that is discussed through the body of work. The backtesting results show that the ES method performs better than all the VaR methods at different confidence levels and recommends that a 95% confidence level should be used. The comparison of the methods further highlights how the methods perform on volatile companies in comparison to slightly steady companies.

The outcomes of VaR and ES methods varies across each company, commodity and confidence level. It was found that the relationship between Monte Carlo Simulation, variance-covariance and historical simulation varies at different confidence levels and companies despite these methods being VaR methods. The possible loss estimates from the historical simulation methods immerge higher than the variance-covariance in some companies while the opposite applied in others. The losses estimated by the ES models were also higher than the VaR in all the companies analysed. The research study recommends that the ES method should be used to determine the possible loses in mining companies as the results of this method performed better than VaR.

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TABLE OF CONTENTS

List of Figures

List of Tables

1. INTRODUCTION

1.1. Research background

Since the mid-2008 Global Financial Crisis, several markets have been negatively affected including commodity markets. The emergence of sophisticated investors and extreme fluctuation in market supply and demand increased the challenges encountered in the commodity markets post the economic recession.

Pilipovic (2007) identified factors specific to the energy commodity markets that distinguish them from the traditional financial markets and these increase the level of risk. The factors include higher volatility, skewed and leptokurtic return distribution, the nature of production and the consumption of energy commodities. The dynamic nature of the energy commodity market signifies the importance of risk management for financial traders, but this extends to energy suppliers and consumers as a risk management strategy applies to operations and investments (Almli & Rege, 2011).

South Africa's energy sector is no different to the global market trends. Mathu and Chinomona (2013) provided a comprehensive analysis of the South African energy sector and its social attributes. 25% of South African's coal production is exported while 75% is used by the domestic market, creating a significant reliance on domestic usage. The average coal export price Free on Board (FOB) increased by 94.5% to R 704,62 per tonne in 2008 as compared to 2007. A similar trend was observed between 2007 and 2008 on the domestic coal prices as they increased by 25% (Mathu & Chinomona, 2013). The price dynamics between domestic and export coal creates a need for a robust measure and management technique given South Africa's reliance on the commodity.

The increased complexity and skills set introduced to the energy commodity markets have driven the utilisation of commodity forecasting models and risk management tools as a mechanism of quantifying energy price risk. Accurate monitoring and mitigation of market risk has become a necessity within commodity risk management. The complexities of today's financial markets necessitate the use of risk modelling to predict extreme losses. In the absence of an adequate risk control system, it can be difficult for firms to reduce fluctuations in returns (Aizaz, 2012).

Several reports by organisations such as Moody's emphasise the need to comprehend the risks that financial and commodity markets are exposed to and the appropriate management mechanisms of the risk exposure. The growth of financial markets globally provides institutions with enormous possibilities to invest, produce and to sell their products in countries other than their native, creating another case for risk management (Khadar, 2011).

As part of the regulation of capital and risk management, the Basel Committee on Banking Supervision (Basel Committee) introduced the use of Value at Risk (VaR) in 1996 and the revised version in 2006 through the Basel Accord (Basel Committee on Banking Supervision, 2011). VaR is a commonly used quantitative tool to measure market risk exposures. One of the critical questions addressed by VaR relates to the value that is lost at a given probability over a pre-set time horizon (Holton, 2017). The inability of VaR to capture information in the lower tail beyond the first percentile is one of its biggest criticism and one of the drivers for alternatives methods such as Expected Shortfall (ES). The use of ES as an alternative to address the problems inherent in VaR models was recommended by Artzner *et al.,* (1997). ES is proposed as an option due to its ability to model possible losses beyond the VaR level and is shown to be sub-additive. VaR disregards losses beyond the percentile and is not sub-additive.

One of the challenges with ES is its practical implementation despite it being mathematically superior to VaR. The increase need for adequate risk measure in commodity markets and the contrasting views of ES and VaR requires an analysis to understand which method is the most appropriate for risk measurement.

1.2. Problem statement

A critical assumption in almost all VaR models is that the risk in a portfolio under evaluation does not change over a specific risk horizon. During the initial application of VaR, the assumption of minimal change to risk was not an issue as the risk horizon was limited to one or two days. Extreme price movements are problematic to capture with the application of VAR as it assumes that an asset's returns follow a normal probability distribution which is not often the case. To address the problems associated with VaR, a more advance method known as Expected Shortfall (ES) was proposed. ES factors losses that exceed the VaR level and measures the expected returns when there is failure in the market or an event that is considered as a risk. The outcomes of ES indicate the expected worst-case scenario. Eriksson (2015) discussed various reasons that make ES a superior risk measurement method as compared to VaR however, the transition of financial regulations from VaR to ES has been slow. The primary reason for the delays in the transition of financial regulation is the lack of consensus on the most appropriate backtesting methods for ES estimates.

Aloui and Mabrouk (2010) concluded that they are far from finding any consensus about the appropriate VaR model for commodity price risk forecasting. This raises the question: *"Which risk management model is most suitable for determining risk exposure in mineral commodities?* ES and VaR models are considered the best and most used risk measures in financial markets but literature indicates that they both have drawbacks.

1.3. Purpose of the study

Several studies have investigated VaR models including the testing of parametric and non-parametric models by Dowd (1998) and Jorion (2000), the findings of these studies have not been consistent. The inconsistency of the VaR models raises a challenge in identify the most optimal risk measurement method. Some literature concludes that the risk measurement model and distributional assumptions depend on several factors including the market under evaluation, the length and frequency of the data series, and the relations between VaR and trading positions (Angelidis *et al.*, 2004; Shao *et al.*, 2009).

VaR is considered conceptually simple however, its implementation is not as straight forward as there are different VaR models with their own advantages and disadvantages. A theoretic comparison of these models provides a clear guidance of the respective short comings of VaR. Empirical analysis is conducted through the study to support some of the proposed literature. Part of the research study also includes understanding the statistical properties of the various company share returns data sets.

This research study investigated the most optimal risk exposure evaluation methods for mineral commodity risk with a focus on coal and gold mining companies operating in South Africa. The interest in coal and gold was due to their overall importance to the South African economy. Coal is the most widely used primary fuel globally with 36% of the global production being used for electricity generation, while 77% of South Africa's energy needs are provided by coal powered stations (Eskom). South Africa is endowed with an estimated 30 billion tonnes of coal representing 3.5% of the world's coal Mineral Resources (Minerals Council South Africa, 2018). Gold has been instrumental to the South African economy over the years employing 112 200 people and accounting for 4.2% of global production in 2017 (Minerals Council South Africa, 2017).

Khadar (2011) highlights that energy commodity markets are one of the most volatile markets and the current drive towards clean energy increases the risk exposure of coal companies. South Africa produced 87% less gold in January 2015 compared with the same month in 1980, estimates suggests that the country will soon need to look beyond gold as a major Mineral Resource despite the overall mineral deposits and employment (Statistics South Africa, 2015). South Africa has an estimated gold Mineral Resources of 592 Mt (Minerals Council South Africa, 2019). This highlights some of the risks faced by gold producers in the country over the years.

1.4. Significance of the research

Risk management in energy and commodity markets is becoming increasingly important. A growing number of the world's energy markets have been liberalised and multinational power exchanges have emerged. Markets are becoming more integrated, and the trading of forward and futures contracts is increasing. Energy markets differ from traditional financial markets due to the nature of production and consumption (Pilipovic, 2007). The volatility of energy commodities is higher, and their return distributions probability tend to be more leptokurtic and skewed. This is illustrated in Figure 1.1, where there is significant variation and fluctuation in prices of domestic coal supplied to Eskom and export coal. This makes risk modelling a challenging and important task for producers supplying to the various markets.

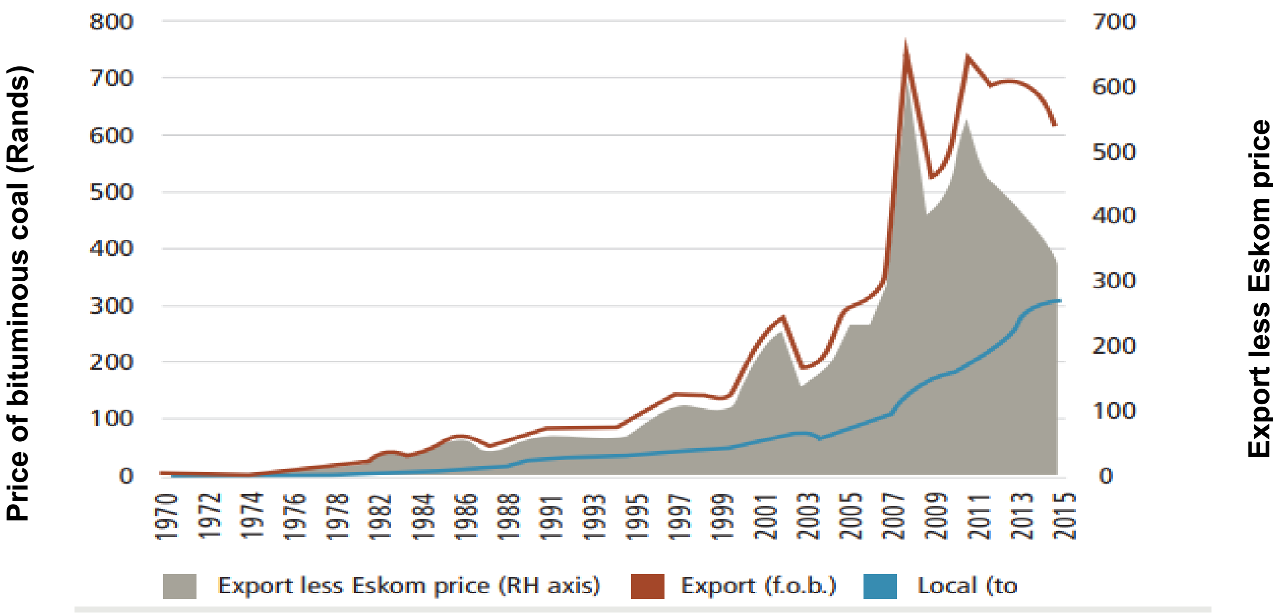


Figure 1.1: Price of bituminous coal in South Africa

Source: Minerals Council South Africa (2018)

Risk management is not only relevant for participants in financial trading, suppliers and consumers of mineral commodities also have a need for hedging of their operations and investments. Over 85,5% households in South African were electrified in 2015 making coal an integral part of primary energy supply in South Africa (Mathu & Chinomona, 2013). This has a direct impact on the national development plans for industries, infrastructure and broader economic growth (Mathu & Chinomona, 2013). The significance of coal to the South Africa economy and dynamic nature of energy minerals requires a clear risk management strategy. Mathu and Chinomona (2013) stated that South Africa is amongst the leading producers of coal globally and the existing reserves could last more than 100 years based on current consumption.

Political and economic events such as Gulf war in the 90s and the mid-2008 Global financial crisis have had impacts on mineral commodity prices increasing their volatility. The mismatch between supply and demand of fossil fuels and mineral commodities is believed to be one of the contributors to volatility. There is a tremendous increase in coal supply with a 3.3% production growth mainly from Russian, India and Indonesia while demand remains constant as countries manage the pressure on global environmental regulations (IEA, 2019). Markets have raised significant concerns over the years due to increases in mineral commodity volatility and risk level.

Market volatility has made risk management indispensable for organisations to survive and succeed in modern economies. This research study gives investors a comparison of various risk evaluation methods through modelling gold and coal companies. The outcomes of these comparison will enable the investor to quantify risk exposures through maximum potentials losses against possible returns.

1.5. Outline of chapters

Chapter 1 has outlined the problem statement and the research question including the aims and research objectives. The literature review is covered in Chapter 2, this includes an overview of the various risk measurement models and some of the considerations associated with their effectiveness. Chapter 3 details the research methodology and tasks carried out in order to address the research question. This includes discussion on the data collection process, modelling and assumptions applied to the research study. Results and discussions are presented in Chapter 4 highlighting the outcomes of the VaR and ES models. Chapter 5 provides a conclusion and recommendations derived from the findings of the research study.

2. LITERATURE REVIEW

2.1. Introduction

This chapter presents an overview of the various risks that are associated with business and emphasis is placed on market risk as this is the most applicable to VaR and ES. The regulations around VaR and ES as outlined in the Basel framework are discussed and a comparison of the two risk measures applied in this research study is provided.

2.2. Risk management

Risk in business is described as the dispersion of unexpected outcomes due to movements in financial variables (Jorion, 2007). The management of risk is often concerned with understanding the risks that prevent an organisation from achieving its strategic goals. There are several types of risk faced by organisations, that include the business environment, regulations and laws, operational efficiency, reputational risk and financial risk (Wood and Dowd, 2008). These risks take different forms and affect organisations differently for example companies operating in different jurisdiction would need to consider the various regulations applicable within the region in which they operate.

The measurement and classification of risk plays a critical role in modern finance and business as this affects organisations differently. The measurement and classification of risk enables organisations to determine their risk appetite and tolerance level. One of the main purposes of risk measurement is to estimate possible future losses of an organisations portfolio and determine the minimal capital requirements to be able to absorb these losses if they occur. Jorion (2007) argued that the monitoring of risk exposure allows organisations to create a better competitive position over their peers.

2.2.1. Types of risk

There are several types of risk exposures in a business such as interest rate risk, exchange rate risk, liquidity risk and equity risk. Mandagelli *et al.* (2001) and Pirrong (2014) defined these risks as discussed below:

- Liquidity risk is a risk that arises due to unexpected substantial negative cash flow over a brief period, this is often caused by selling of assets at a lower value. Stressed markets contribute to the liquidity of companies as assets and inventory are forcefully sold off to change a firm's position. Liquidity varies across commodities and time periods; for example, coal derivatives markets are substantially less liquid than oil derivative markets. Losses are often experienced during the process of managing liquidity positions as sales and purchases drive prices in opposite directions;
- Operational risk is defined as a failure of some operational processes. The financial sector often attributes this type of risk to errors caused by banking personnel or systems including fraud and regulations. Similar attributes can be identified in any industry including commodity trading. A common operational risk in mineral commodities can be traced in invoices related to material stock levels;
- Credit risk relates to the potential loss due to the impossibility of a partner to cover their duties of repaying a loan and interest. It has three basic components namely; credit exposure, probability of default; and loss in the event of the default; and
- Market risk is the risk that arises due to uncertainty of future earnings as a result of changing conditions in the market. This risk is mainly affected by volatility in interest rates, equity, foreign currency and commodity prices that change the value of a company's assets and liabilities.

The primary focus of this research study is on market risk as commodity traders are mostly affected by exchange rate, commodity prices and interest rate fluctuations. These are areas that are often beyond the control of the commodity trader, however, have an impact on the business.

2.2.2. Classification of market risk

The Basel Committee classifies market risk as classified by Mandagelli *et al.* (2001) and Pirrong (2014), except that it does not include commodity prices. The exclusion of commodity prices is alluded to the fact that the Basel Committee governs commercial banks. The subcategories of market risk can be defined as follows (Basel Committee on Banking Supervision, 2004):

- Interest rate risk is the exposure of a company's financial condition to adverse movements in interest rates. Banks often accept this as normal practice as this is a source of profitability, however excessive interest rate risk can pose a significant threat to earnings and capital base. The change in interest rates affects a company's earning by changing the net interest income and the level of other interest sensitive income and operating expense. Changes in interest rates also affect the underlying value of the company's assets, liabilities, and off-balance-sheet (OBS) instruments because the present value of future cash flows (and in some cases, the current cash flows themselves) change when interest rates change. Accordingly, an effective risk management process that maintains interest rate risk within prudent levels is essential to the safety and soundness of a company;
- Foreign exchange rate risk is the risk that the value of an assets or liabilities changes due to currency exchange rate fluctuations. Exchange rate risk consist of the risk of depreciated value of foreign assets portfolio after the adverse changes in the exchange rates and the risk of sign financial agreements of future converting the foreign value, when future exchange rates are stated. Abor (2005) provided three types of foreign exchange risks encountered in the banking sector namely transaction which relates to financial commitments, economic which is a combination of operational, competitive or cash flow challenges and translation which relates to accounting principles; and
- Equity risk is a risk that arises when a when assets included in a portfolio have a market value (securities). The change of the market price of such assets will affect the respective company value.

The most significant uncertainty in commodity trading is market risk as some mineral producers such as gold are subjected to price uncertainty. Price uncertainty often arises in mineral commodity trading due to the price taking nature of the business. Commodities such gold are traded on markets that have predefined prices resulting in producers accepting a given price. Mining companies operating in South Africa are further subjected to exchange rate movements that affect the overall value and exposure of a company's assets. The concern with exchange rates arises when mining companies require imported goods during periods where the Rand is weak.

2.3. Basel Committee on Banking Supervision

The Basel Committee was initially known as the Committee on Banking Regulations and Supervisory Practices. The committee was established by the central bank governors of the group of ten countries following extreme changes in global currency and banking markets particularly the collapse of Bankhaus Herstatt in West Germany (Basel Committee on Banking Supervision, 2018). Financial institutions are supervised by this committee following its establishment in 1974 and the compliance to the regulations outlined by the committee is mandatory.

The regulations of the Basel committee are documented in a series of three Basel Accords which are Basel I, Basel II and Basel III. The accords detail the regulations that were developed over the years by the Basel Committee from as far back as the 1980s (Basel Committee on Banking Supervision, 2013). Part of the Basel Committee regulations include capital requirements as part of market risk management (Basel Committee on Banking Supervision, 2013). The committee emphasise that market risk is a significant challenge and should be integrated into the capital framework of risk measurement. Value at risk methods have been recommended for determining the market risk capital requirements, through the 1996 market risk amendments to the Basel accord.

2.3.1. Basel I

The Basel I accord was issued in 1988 and prescribes the minimum capital required from institutions globally for credit risk. The accord categorises the assets of financial institutions into five risk categories, namely 0%, 10%, 20%, 50% and 100% (Basel Committee on Banking Supervision, 2013). Organisations are required to have adequate capital to mitigate credit risk exposure (Jorion, 2007). The prescribed ratio of capital to weight risk exposure of an asset should be 8% or less, this followed the realisation that the capital adequacy of international financial institutions was deteriorating at a time of growing international risk.

The Basel I accord has gone through two amendments; the first amendments were in 1991 aimed at defining the general provisions of loan losses that should be included in the determination of capital adequacy. In 1995, another amendment was issued in recognition of the effects of bilateral netting of a bank's credit exposure and other forms of risk exposure other than credit risk (Basel Committee on Banking Supervision, 2013). The market risk amendments of the Basel I accord allowed banks for the first time to determine the capital adequacy using Value at Risk models. The conditions for applying this model were subject to strict quantitative and qualitative standards defined by the bank (Basel Committee on Banking Supervision, 2013).

2.3.2. Basel II

Basel II accord was issued in 2004 to replace the initial regulations that were issued through Basel I. The main drivers for developing the second accord was to account for the changes in the financial sectors and prescribe a model that can adequately reflect the underlying risk in the regulatory capital requirements (Basel Committee on Banking Supervision, 2013). The Basel II enforces three pillars (Jorion, 2007):

- Minimum regulatory requirements aimed at risk exposure. This is an enhancement of the rules set out in Basel I;
- Supervisory review that expands on the role of institutions to ensure that there is compliance to the regulations; and
- Market discipline that requires companies to share their company specific risk. This was intended to strengthen market discipline and encourage common practice amongst organisations.

The challenge with the application of the Basel II was the need for organisations to approve the use of certain approaches to risk measurement in multiple jurisdictions. Basel II identifies VaR analysis as the accord's preferred tool for assessing the exposure to market risk of a bank (Basel Committee on Banking Supervision, 2004).The main concern was the extended scope of risk evaluation methods approvals and the demand for a greater degree of cooperation between home and host supervisors (Basel Committee on Banking Supervision, 2013).

2.3.3. Basel III

Basel III requires daily risk forecasts derived by companies to be communicated to appropriate monetary authorities prior to each trading day. The third accord recognised the incoherence of VaR as a risk measure and proposed Expected Shortfall (ES) method as an alternative given the coherence of the method (Basel

Committee on Banking Supervision, 2011). The consultative document issued by the Basel Committee in May 2012 highlights the prospect of phasing out VaR and replacing it with ES. VaR and ES models analyse a company's risk exposure over a given confidence level and specific time frame (Basel Committee on Banking Supervision, 1996). Butler (1999) indicated that VaR assists the Basel Committee with the development of a risk management system designed to reduce the probability of collapsing of financial institutions.

Financial institutions are often responsible for damages related to poor management of risk (Butler,1999). The Basel committee recognised the need to standardise the risk management systems in order to identify the specific risk exposure and to transform the computed risk value between institutions. A consultative document was published by the Basel Committee in 2013 presenting a proposal on capital requirement policies. The main discussion points include the transition of quantitative risk metrics system from VaR to ES and decreasing the confidence level from 99% to 97.5% (Basel Committee on Banking Supervision, 2013). The document highlighted the weakness in using VaR as risk measure for regulatory capital requirements including its failure to capture tail risk.

According to the capital adequacy directive which incorporates a report by the Basel Committee on Banking Supervision (1996), the risk capital of a bank must be sufficient to cover losses on the bank's trading portfolio over a 10-day holding period on 99% of occasions. Confidence levels generally range between 90% and 99%, rather than choosing a single parameter, some organisations use several confidence levels (e.g. 95% and 99%) and forecast horizons (e.g. 1 day and 1 year). Risk Metrics assumes 95% confidence as a baseline but gives users the flexibility to choose other levels (Laubsch, 1998).

2.4. Risk evaluation models

The sub-sections below provide a detailed overview of VaR methods and ES as these methods are the primarily used to measure market risk in modern day finance. The VaR methods are discussed highlighting the difference between parametric, semi-parametric and non-parametric VaR.

2.4.1. Value at risk (VaR) models

The use of VaR dates as far back as 1952 with the work published by Markowitz and Roy. Holton (2002) provides a contrast of some of the work that contributed to the early development of VaR. Markowitz (1952) used a range of simple returns while Roy (1952) used a metric of shortfall risk depicting the upper limits of a portfolio to show the effects of hedging and diversification in relation to overall risk exposure. The objective of their work was to find ways of optimising profits at a given risk level. Some of the precursors to VaR included Standard Portfolio Analysis of risk developed by Chicago Mercantile Exchange for setting future margins, this was mostly used by commodity traders (Culp *et al.*, 1998).

Although the first publications about the predecessors of VaR dates to the 19th century, the credit for the use of the current VaR methodology is attributed mainly to United States of America investment bank JP Morgan (Adamko *et al.,* 2015). VaR is a tool in risk management used for measurement of risk by commodity traders, banks and financial institutions developed by JP Morgan in 1993. Originally VaR was intended to measure the risks in derivatives markets however, it is being extensively applied by financial institutions to measure all kinds of financial risk (Adamko *et al.,* 2015).

Chen (2014) highlighted that VaR has been endorsed by authorities around the world such as the European Commission and the Federal Deposit Insurance Corporation, either as a regulatory standard or as a best practice. Even with absent regulatory compulsion, private firms routinely use VaR as an internal risk management tool, often directing traders to reduce exposure below the level prescribed by those firms' own VaR limits (Chen, 2014).

Before VaR, most commercial trading houses focused mainly on desk by desk risk as opposed to overall company exposure (Chen, 2014). The introduction of VaR enabled these trading companies to develop risk measures that can be aggregated and compared across various trading platform as a means of measuring and managing overall exposure. One of the key reasons for the introduction of VaR was to systematise the measure of overall company's risk exposure across its entire dealing portfolio as opposed to single transaction.

Basel III describes VaR as a risk measure for the calculation of minimum capital requirement in line with potential losses under the market risk framework. Holton (2002) considered VaR to be a category of probabilistic measure of market risk. This metric is a function of the distribution of returns and the current market value of the portfolio. Acerbi and Tasche (2001) defined VaR as the minimum potential loss that a portfolio can suffer in the 1% worst case in a set time period.

Figure 2.1 can be used to describe VaR which is the maximum loss that a portfolio or entity will experience over a given time interval (*t*) and confidence level (*c*) (Mak and Meng, 2014). Analysis of risk in a portfolio takes into account the current value and forecasts the worst and best case scenario over time. VaR is interested in managing the expected worse case which results in a drop on the current value as illustrated in Figure 2.1.

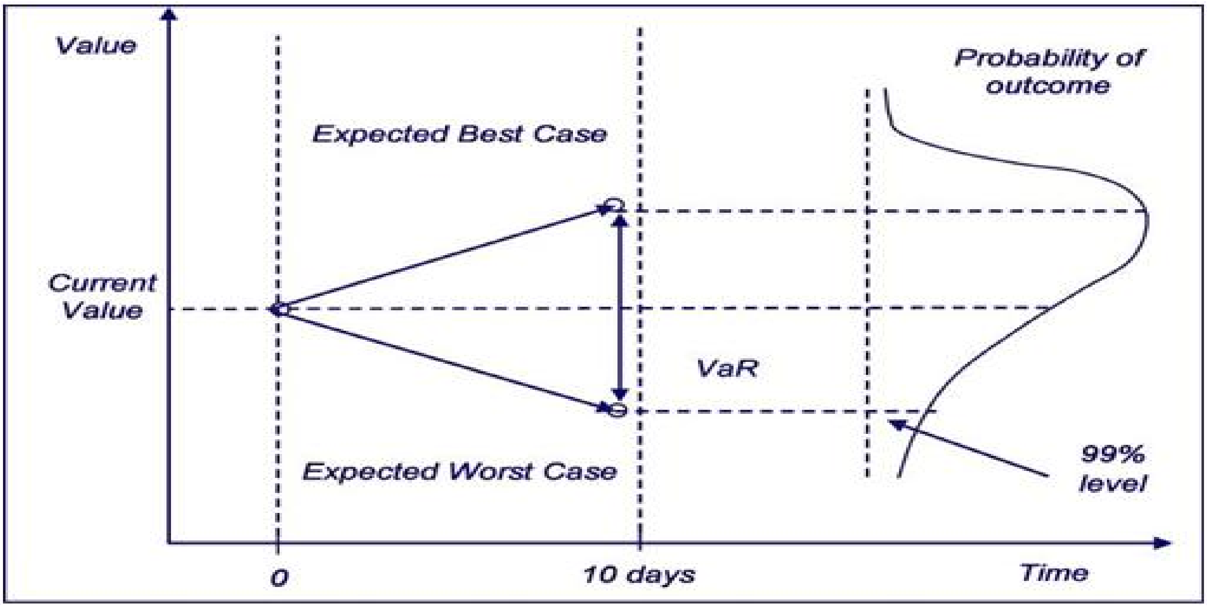


Figure 2.1: Value at Risk illustration

Source: (Farid, 2010)

A specified level of loss in value, a fixed time period over which risk is assessed and a confidence interval are the three key elements of VaR. The VaR can be specified for an individual asset, a portfolio of assets or for an entire firm. Statistically, VaR can be presented as in Equation 1 according to Jorion (2007).

$$P(L > VaR) \leq 1 - c \tag{1}$$

Where:

P represents the probability of loss;

c represents the level of confidence usually set at 95 % or 99 %; and

L refers to the total loss of the portfolio.

Mak and Meng (2014) denoted VaR as in Equation 2:

$$VaR_c(Z) = \sup \{z_t | \ P(Z \geq z_t) > c\} \quad (2)$$

Where:

z_t represents the (1-c) th quantile of the distribution;

Z represents the loss function; and

c represents the confidence level.

VaR's popularity is owed to its simplicity and its ability to compute risk as a single figure that represents overall potential losses with a specified confidence level in currency terms (Mak and Meng, 2014). As a result, it is easy to understand, intuitive to manage and regulate. VaR has received widespread accolades from industry and regulators with numerous organisations finding that the practical uses and benefits make it a valuable decision support tool in a comprehensive risk management process (Culp *et al.*,1998).

There are three types of methods with their own variations that can be used to compute VaR. Manganelli and Engle (2001) distinguished these computational methods as parametric, semi-parametric and non-parametric. Parametric methods are used to determine the return distributions for market risks while semi-parametric calculate the variances and co-variances across the market risks. Hypothetical portfolios are modelled through non-parametric methods using historical data or Monte Carlo-Simulations.

2.4.1.1. Parametric VaR models

Parametric (analytical) VaR-methods are methods such as generalised autoregressive conditional heteroskedasticity (GARCH) and variance-covariance method. These methods use parameterisation of the time-varying stochastic behaviour of financial prices. GARCH was introduced by Bollerslev (1986), who based his work on the autoregressive conditional heteroscedasticity (ARCH) model by Engle (1982). In order to estimate the parameters in this model framework, an error distribution must be assumed. The normal probability distribution was originally suggested (Bollerslev,1986). This is the easiest probability distribution to implement, and it is very often used at least as a benchmark. Even though the normal distribution is simple and popular, it has been shown empirically that it is often unsuitable for real world applications. The distribution of financial returns tends to be leptokurtic; it has heavier tails than predicted by the normal distribution, as well as more returns close to zero (Bollerslev, 1986).

The variance-covariance method recognises that the distribution of returns for a portfolio are normally distributed and the relations between the risk and the portfolio is linear. This method includes parts of modern portfolio theory of Harry Markowitz, by taking account of correlation coefficients between assets (Corkalo, 2011). The application of the variance-covariance method includes the determination of the portfolio returns and these are used to determine the mean, standard deviation and correlations. The volatility of can be described using the standard deviation because this method assumes a normal theoretical distribution. The descriptive statistics are determined by using the historical data. Part of the process includes estimation of the portfolio VaR using the covariance matrix (i.e. the estimated variances and covariances) and the weights on the standardised positions (Jorion, 2007). Corkalo (2011) presented the variance-covariance formula as shown in Equation 3:

$$VaR = ZVP \tag{3}$$

Where:

Z is the standard value (calculated from confidence level using formula "NORMSINV" in Microsoft Excel);

V is the volatility of standard deviation of the asset; and

P is the position (portfolio) value.

The advantages and disadvantages of the variance-covariance method are consequences of the underlying assumptions on which the method is based on. The assumption about the linear relationship among market risk factors is the advantage of the method while the assumption that portfolio returns are joint normally distributed is the main disadvantage of this method (Katsenga, 2013).

2.4.1.2. Semi-parametric VaR models

Semi-parametric VaR models include extreme value theory (EVT) and quantile regression (QR) which model the quantile directly instead of modelling the whole probability distribution. The challenge with these models is the assumption that returns are independent and identically distributed which is not always the case. Filters are often applied to address some of these problems before modelling, to remove the disadvantage of modelling risk directly (Kuester *et al*., 2006). Embrechts *et al.,* (1998) provided a further analysis on some of the challenges associated with semi-parametric models.

Monte Carlo Simulation is one of the semi-parametric methods and is often used in complex estimations that require high confidence levels (Katsenga, 2013). The real power of Monte Carlo Simulation is in more complex settings, where instruments are non-linear, prices are path dependent and distributions do not have well defined inverses. The method does not rely on assumptions related to probability distribution of returns thus making it an optimal method to capture fat tails. The application of this method includes defining the financial variables, modelling volatilities and correlations using historical data. Random numbers are then generated using the defined financial variables. The price realisations from the simulation are then compiled to a joint distribution of portfolio returns wherein VaR estimates are then computed (Dowd, 1998).

The main drawback of standard VaR estimation method is the inability to measure extreme price movements. Engle and Manganelli (2004) noted that standard VaR models assume that assets follow a normal probability distribution which is not the case due to volatility over time. This disregards the fat-tailed properties of actual returns and underestimate the probability of extreme price movements. Traditional VaR fails to capture the shifts in volatility or volatility clustering (Noshkov and Demirtas, 2017).

2.4.1.3. Non-parametric VaR models

Non-parametric methods have no restrictions that results from assumptions of normality and estimation of parameters based on historical data. One of the advantages of this method is its robustness to the model assumptions (Corkalo, 2011). Historical simulation is an example of non-parametric VaR methods as the method uses historical distribution of a portfolio to simulate the VaR. The VaR value is estimated by reading the required confidence from the portfolio distribution. The method requires sufficient historical data for simulation which is often a challenge when assessing new assets. The basis of this method is the assumption that a portfolio will remain constant during the period under review therefore making the returns a reliable proxy for future projections, this is supported by Dowd (1998). One of the limitations of this method is that it assigns the same value to current and older data, this can cause bad estimates if there are recent trends, such as higher volatility, this high volatility will not be captured (Corkalo, 2011).

Corkalo (2011) argued that the correct method of determining VaR using historical simulation entails determining the historic price change and apply them to the current share prices as follows:

- Determine the price change or logarithmic returns for every asset or risk factor required to revalue the asset or portfolio;
- Apply price changes to the portfolio to generate a “historical” series of portfolio value changes and sort the portfolio value changes into percentiles; and
- Determine the final VaR of the portfolio which is the return that corresponds to the required confidence level.

2.4.1.4. Summary of VaR models

Table 2.1 provides a comparison of VaR methods looking at its ability to capture risk, ease of implementation, computational speed and ease of explaining the outcomes of the model. Despite the accolades of VaR, several issues related to the application of VaR are covered by (Bradley and Taqqu, 2003; Dowd, 1998). Results from VaR models are contradictory in terms of the accuracy of the models proposed with plenty of discussions focusing on whether simpler models can outperform the more complex flexible ones. Brooks and Persand (2003) found that simple models achieved comparably better VaR forecasts as compared to more complex ones such as Monte Carlo Simulation. Mittnik and Paolella (2000) showed that more accurate VaR forecasts can be achieved with more flexible models such as variance-covariance. Simple models often lead to underestimation of the VaR, whereas the opposite holds for the more complex models that seem to lead to overestimation of the VaR.

Table 2.1: Comparison of Value at Risk methodologies

Evaluation Criteria	Historical Simulation	Variance/Covariance	Monte Carlo Simulation
Able to capture the risks of portfolios which include options?	Yes, regardless of the options content of the portfolio.	No, except when computed using a short holding period for portfolios with limited or moderate options content.	Yes, regardless of the options content of the portfolio.
Easy to implement?	Yes, for portfolios for which data on the past values of the market factors are available.	Yes, for portfolios restricted to instruments and currencies covered by available "off-the-shelf" software. Otherwise reasonably easy to moderately difficult to implement, depending upon the complexity of the instruments and availability of data.	Yes, for portfolios restricted to instruments and currencies covered by available "off-the-shelf' software. Otherwise moderately to extremely difficult to implement.
Computations performed quickly	Yes	Yes	No, expect for relatively small portfolios.
Easy to explain to senior management	Yes	No	No

Source: Linsmeier and Pearson (1996)

Extreme events do not occur frequently enough to generate adequate data hence the use of a combination of positive and negative returns. The disadvantage of combining returns affects the results as extreme events have much higher means and variances. If VaR is calculated using extreme events, it would lead to a much higher value at risk estimate.

VaR has been criticised because it lacks coherence in general (although it is coherent for some classes of distributions, e.g., elliptically contoured distributions) and ignores losses beyond the VaR level. VaR does not provide an estimate of the loss severity, should a suitably large loss occur (as determined by the confidence level), it only provides a measure of the loss frequency (Acerbi & Tasche, 2001). More importantly, VaR is not sub-additive meaning that it penalises diversification instead of rewarding it. As a result, a new risk measure, namely Expected Shortfall (ES) was advanced and is discussed in the next section as an alternative.

2.4.2. Expected Shortfall (ES) models

Expected Shortfall (ES) is the probability-weighted average of the loss that exceeds VaR. Artzner *et al.,* (1997) introduced ES once it was found that VaR is not coherent. Acerbi & Tasche (2001) indicated that it is a superior risk measure when compared to VaR as it is sub-additive and coherent. A more general version of the ES and proof of sub-additivity was found by Acerbi and Tasche (2001) following gaps in the definition provided by Artzner *et al.,* (1997) relating to sub-additivity for discontinuous functions. Sub-additive risk measure means that the combined risk measure for a portfolio cannot be greater than the sum of the risk measure for the individual parts of the company portfolio (Artzner *et al.,* 1997). Acerbi and Tasche (2001) considered this to be one of the attractive properties of ES as a risk measurement method.

ES can be used as a measure of VaR performance in at least two ways (Angelidis & Degiannakis, 2006). Firstly, as a comparable value, against which for example the average VaR forecast is compared, to verify whether the risk beyond VaR is great for a given market. Lastly, an ES based loss function can be used to choose the best VaR model (Angelidis & Degiannakis, 2006). The problem with using ES in this way is that the accuracy of the ES models is not tested.

Ho *et al.* (2008) indicated that ES can be illustrated through mean excess loss (MEL), which is the conditional expectation of a loss given that the loss is beyond the VaR level. Equation 4 is used to calculate MEL:

$$MEL = E[R(\Delta t) - VaR | R(\Delta t) > \mathrm{VaR}] \quad (4)$$

ES can therefore be calculated as a prudent measure of the margin level as shown in Equation 5 (Ho *et al.*, 2008):

$$ES = E[R(\Delta t) - VaR|R(\Delta t) > \mathrm{VaR}] = \mathrm{VaR} + MEL = ML^{short} \quad (5)$$

Where:

E represents the conditional expectation;

$R(\Delta t)$ represents the percentage price changes of a future contract over a time period of Δt; and

ML^{short} represents the marginal level.

This formula can be redefined as shown in Equation 6 (Mak and Meng, 2014):

$$ES_c(Z) = E[Z \mid Z \geq VaR_C(Z)] \quad (6)$$

Where:

ES_c represents the Expected Shortfall at a confidence level c;

Z is a continuous loss distribution;

E[Z|A] represents the expectation of Z given event A as articulated by Mak and Meng (2014).

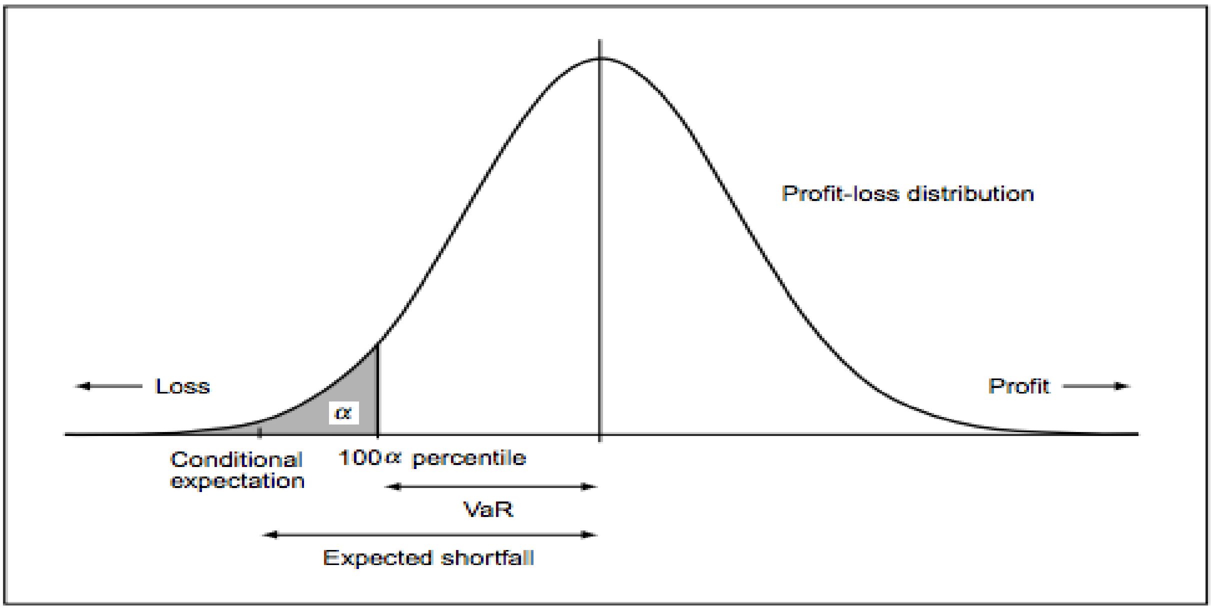


Figure 2.2: Profit-loss distribution, VaR and Expected Shortfall

Source: (Yamai & Yoshiba, 2002)

Figure 2.2 depicts a comparison of ES and VaR using a hypothetical portfolio with a normal distribution of returns. The figures on the left-hand side of the mean represent losses on the portfolio over the trading period under review. Interpreted graphically, the Value at Risk of the portfolio is measured as the value that corresponds to the figure at the lower tail of the distribution. This would be the loss corresponding to α in the figure above. Expected Shortfall would be losses that correspond values greater than confidence level α.

Several studies comparing VaR and ES focus on the differences in theoretical framework, and how ES is a better and coherent risk measure. Yamai and Yoshiba (2005), on the other hand, tried to decide which risk measure is best by comparing their performance in currency markets. They concluded that VaR and ES should be used together, since VaR has the problem of disregarding losses beyond the VaR point, while ES has much greater estimation errors than VaR and is therefore more difficult to model accurately. Some of the short comings of ES identified by Yamai and Yoshiba (2002) are that the method needs a larger sample size to achieve higher accuracy levels and the inconsistency with right tail risk.

2.5. Backtesting of risk models

VaR models are only useful in as far as they can be demonstrated to be reasonably accurate (Jorion, 2007). As part of verifying the accuracy of risk models, backtesting was one of the recommendations derived from literature (Jorion, 2007; Basel Committee on Banking Supervision, 1996). The Basel Committee advocates for backtesting as a critical part of the internal model's approach to market risk management (Basel Committee on Banking Supervision, 1996).

Backtesting is a formal statistical framework that consists of verifying that actual losses are in line with projected losses (Jorion, 2007). The purpose of backtesting is to determine the accuracy of the risk models. Katsenga (2013) indicated that there are several methods that have been and continue to be proposed to validate results derived from risk models, these include stress testing, independent review, and oversight, amongst others.

The most widely known and used test based on failure rates is the Kupiec test which is best applied as a likelihood-ratio test. According to statistical decision theory, likelihood-ratio test is the most powerful test in its class (Jorion, 2000). The Basel Committee proposed the Traffic light approach as a preliminary backtesting method to be used by organisations as part of their internal VaR models. The traffic light test will be used together with the Kupiec test as these are traditional methods and most suitable for the objective of this research study.

2.5.1. Kupiec Test

Kupiec (1995) introduced the unconditional coverage likelihood ratio tests as an inference tool for whether the VaR model generated the correct number of exceptions. Unconditional coverage ignores exceptions as they occur but focuses mainly on the frequency of the exceptions (Jorion, 2007). If the frequency of exceptions are less than the corresponding confidence level, it indicates that the VaR models overestimates the market risk. Too many occurrences indicate an underestimation of the market risk (Khadar, 2011).

Kupiec's test is also referred to as the proportion of failures (POF) test. It measures whether the number of exceptions are consistent with the confidence level. The null hypothesis (H_0) for the proportion of failure is depicted in Equation 7:

$$H_0 : p = \acute{p} = \frac{X}{T} \tag{7}$$

Where:

p is the failure rate suggested by the confidence level;

ṕ is the observed failure rate;

X is the number of exceptions; and

T is the number of observations.

The main objective of the null hypothesis is to prove the accuracy of the model and determine whether the observed failure rate ṕ is significantly different from p. The model uses the following data inputs to run the POF test, namely confidence level *(c),* number of observations (T) and number of exceptions (x) (Dowd, 2005). Equation 8 shows that the likelihood ratio test can be statistically presented as (Kupiec, 1995).

$$LR_{POF} = -2\ln\left(\frac{(1-c)^{N-x}c^{x}}{[1-(\frac{x}{N})]^{N-x}(\frac{x}{N})^{x}}\right) \tag{8}$$

Where:

N represents the number of trading days/ time horizon;

C represents the confidence level; and

x represents the realised exception.

Equation 8 can be redefined as shown in Equation 9 (Katsenga, 2013).

$$LR_{POF} = -2ln\,[(1-c)^{(N-x)}c^{x}] \; + \; 2ln[(1-\frac{x}{N})^{(N-x)}(\frac{x}{N})^{x}\,] \tag{9}$$

Table 2.2 indicates the various confidence levels *c* and the corresponding acceptance regions for the number of failures. The table highlights that the POF-test increases its computing power as the sample size increases. Larger trading days allow the test to reject incorrect outputs more easily.

Table 2.2: Non rejection regions for POF-test under different confidence levels and sample sizes

Probability Level (p)	VaR Confidence Level	Non-rejection Region for Number of Failures (N)		
		T = 250 days	T= 510 days	T= 1000 days
0.01	99%	N <7	1 < N < 11	4 <N < 17
0.025	97.5%	2 < N<12	6 < N < 21	15 < N< 36
0.05	95%	6 < N < 21	16 < N < 36	37 < N < 65
0.075	92.5	11 < N < 28	27 < N < 51	59 < N < 92
0.1	90%	16 < N < 36	38 < N < 65	81 < N < 120

Source: Kupiec (1995)

This method of testing measures is considered as simple to implement however, there are two main drawbacks. First, as pointed out by Kupiec (1995; 2005), when the number of trading days used in VaR evaluation is limited (e.g. one year or approximately 250 trading days), or when the confidence level is high (e.g. 99% as in regulatory VaR), such tests have low power. The second drawback is that the test only measures the failure rate and not the success of occurrences. It may fail to reject a model that produces serially dependent violations, this is a common weakness of unconditional coverage models (Katsenga, 2013).

2.5.2. Basel Committee Traffic light test for VaR

The Basel Committee requires banks with a significant portfolio to reserve capital sufficient to cover potential losses that may arise due to market risk. The amount of market risk capital (MRC) is determined by the banks VaR estimates. The regulatory risk based capital requirements are a function of the larger value of either the bank's assessment of the 99% confidence level VaR over a 10-day holding period or a multiple of the bank's average reported 99% confidence level VaR over the preceding 60-day holding period plus an additional amount that reflects the underlying credit risk (c) of the bank's portfolio (Basel Committee,1996). Equation 10 illustrates MRC.

$$MRC_t = \max\left[VaR_t(0.99), k\frac{1}{60}\sum_{i=0}^{59} VaR_{t-i}(0.99)\right] + c \qquad (10)$$

Where:

k represents the multiplication factor that is applied to the average of previously reported VaR estimates;

c represents confidence; and

t represents time period.

The multiplication factor k varies with the results of the backtesting. The multiplication factor, k, is determined by classifying the number of 99% VaR exceptions, x, in the previous 250 trading days. The exceptions are classified into three distinct categories as shown in Table 2.3.

Table 2.3: Classification category for multiplication factor

Factor	Rating	Formula	Code
k	3	$x \leq 4$	Green
	$3 + 0.2\,(x-4)$	$5 \leq x \leq 9$	Yellow
	4	$10 \geq x$	Red

Source: Basel Committee on Banking Supervision (1996)

The three zones have been delineated and their boundaries chosen in order to balance two types of statistical error (Basel Committee on Banking Supervision, 2016):

- The possibility that an accurate risk model would be classified as inaccurate based on its backtesting result; and
- The possibility that an inaccurate model would not be classified as inaccurate based on its backtesting result.

The green zone corresponds to backtesting results that do not suggest a problem with the quality or accuracy of a VaR model. The yellow zone encompasses results that do raise questions on the accuracy of the result, but the conclusion is not definitive. The exceptions in the yellow zone ranges from five to nine. These outcomes could be produced by both accurate and inaccurate models with relatively high probability, even though they are likely inaccurate models. Backtesting results in the yellow zone generally cause an increase in the multiplication factor, depending on the number of exceptions. However, these increases are not purely automatic since yellow zone does not necessarily imply an inaccurate model. If an organisation can demonstrate that the VaR model is ‘fundamentally sound’ and suffers, for example, from market misfortune, supervisors may consider revising their requirements.

The red zone indicates a backtesting result that almost certainly indicates a problem with a risk model. Red zone generally indicates a clear problem with the VaR model. As can be seen from Table 2.4, there is a small probability that an accurate model would generate 10 or more exceptions from a sample of 250 observations. As a result, red zone should usually lead to an automatic rejection of the VaR model. (Basel Committee on Banking Supervision, 1996).

The zones shown in Table 2.4 are based on a sample of 250 observations. The cumulative probability is the probability of obtaining a given number or fewer exceptions in a sample of 250 observations when the model is correct (i.e. true coverage level is 99%).

Table 2.4: Traffic light approach

Zone	Number of exceptions	Increase in scaling factor	Cumulative probability
Green zone	0	0,00	8,11%
	1	0,00	28,58%
	2	0,00	54,32%
	3	0,00	75,81%
	4	0,00	89,22%
Yellow zone	5	0,40	95,88%
	6	0,50	98,63%
	7	0,65	99,60%
	8	0,75	99,89%
	9	0,85	99,97%
Red zone	10 or more	1,00	99,99%

Source: Basel Committee on Banking Supervision **(1996)**

One of the draw backs of the Traffic light approach is its failure to consider clustering of expectations, this is one of the reasons why this approach cannot be used to evaluate the extensive accuracy of VaR model. This approach struggles to distinguish good VaR models from bad ones. This shortcoming of the framework is acknowledged by the Basel Committee (1996). This method is mostly used for internal purposes or as a preliminary test for the accuracy of VaR models (Katsenga, 2013).

Costanzio & Curran (2018) defined a Traffic light approach to backtest ES using the outcomes of Costanzino and Curran (2015). The test is an extension of the VaR breach indicator to the case of ES as seen in Table 2.5. The breach indicator for Expected Shortfall is a continuous variable, the quantile selected and then invert to obtain the corresponding breach value. The breach values and cumulative probabilities for Expected Shortfall at the 97.5 quantile (i.e. α = 2.5%) are very similar to the VaR values at the 99 quantile (i.e. α = 1%).

Table 2.5: Traffic light approach to ES

Zone	Generalized Breach Value	Cumulative probability
Green zone	0	0.18%
	1.3929	10%
	2.1131	25%
	3.0276	50%
	4.0520	75%
	5.0622	90%
	5.7049	95%
Yellow zone	5.7049	95%
	6.9844	99%
	8.5285	99,9%
	9.8833	99,99%
Red zone	More than 9.8833	99,99%

Source: Costanzio and Curran (2018)

2.6. Chapter summary

The chapter provided an overview of market risk which is one of the focus areas for risk management. The primary mechanism for quantifying this type of risk is through VaR methods, however ES was introduced to manage some of the short coming identified. The next chapter provides details on the application of the identified VaR methods and ES model.

3. RESEARCH METHODOLOGY

3.1. Introduction

The study focuses on the comparison of VaR and ES models for selected minerals commodities. This chapter provides the details on the data and methodology applied in comparing the VaR and ES models for the selected group of coal and gold mining companies. Section 3.2 describes the sources of data and nature of the data required for this study. The parameters used to estimate and apply the various formulae are discussed in Sections 3.3 and 3.4.

3.2. Data from JSE-listed mining companies

This research study is limited to coal and gold mining companies listed on the Johannesburg Securities Exchange (JSE). The JSE was selected as a primary source of data because it complies with global standards and legislative requirements. The data set provided by the JSE covers various financial cycles and ensures that listed companies provide reliable information. The JSE data is available in the public domain.

The primary data used for this research study were the adjusted daily closing share prices for the various companies listed on the JSE with a focus on the last 5-year period from 2015-2019. Frequently traded instruments like gold and coal require a shorter time horizon hence the use of daily returns (Harmantzis *et al*.,2005). A study conducted by Alexander (2008) on the S&P 500 during the financial crisis period found that there was high levels of volatility on the data set and the VaR models traditionally used proved to be inaccurate during these periods. The period of 2015-2019 was considered because it covers a period post the Global Financial Crisis, which had a significant impact on mining share prices. A less volatile period would allow VaR models to be tested without the influence of excessive volatility. To achieve features representative of a normal distribution curve, one is required to use historical data from at least 5-6-year period (Adamko *et al.,* 2015).

The natural logarithm (ln) of the daily returns was used in the analysis as log normal returns lend themselves to the advantage of being able to construe accurate results irrespective of the horizon under consideration (Chotee, 2014). The adjusted daily closing prices were used to calculate the daily returns as indicated in Equation 11.

$$R_i = \ln(\frac{N_t}{N_{t-1}}) \tag{11}$$

Where:

R_i represents the returns for the stock i*;*

N_t represents the stock price for the day; and

N_{t-1} *r*epresents the stock price for the previous day.

The study focused on blue collar coal and gold mining companies with assets in South Africa and a primary listing on the JSE. Gold was selected as one of the commodities for this research study as it is considered as a safe haven and coal remains the main source of power in South Africa. South Africa has a significant amount of gold and coal Mineral Resources as dicussued in previous chapter. Companies were selected based on their listing as part of the JSE Top 100 and the limited diversity in the commodities within a company portfolio. The coal and gold companies that were analysed for this study are:

- Gold: Anglo Gold Ashanti Limited (AGA), Gold Fields Limited (GLI) and Harmony Gold Mining Company (HAR);
- Coal: Exxaro Resources Limited (EXX) and Sasol Limited (SOL).

The primary data collected for this research were daily adjusted closing price sourced from Sharenet and Bloomberg databases. The adjusted closing prices are used as they account for stock splits and dividend returns which are a better indicator of the share performance. To ensure that adequate results are obtain for the risk models, literature indicates that a longer window period yields more reliable results (Harmantzis *et al.,* 2005). Aizaz (2012) argued that the period representative is a critical factor as this period should be reflective of the actual risk associated with the commodity, hence the decision to consider the period post Global Financial Crisis.

The study was guided by Swami *et.al.* (2016) discussion on the implementation of internal models' approach for market risk. In order to calculate VaR, the following recommendations were proposed in the Prudential Guidelines on Capital Adequacy (Basel Committee on Banking Supervision, 2011):

- VaR should be calculated based on daily returns;
- The 99^{th} percentile and one-tailed confidence interval should be used; and

- An instantaneous price shock equivalent to a 10-movement in prices is to be used, that is, the minimum 'holding period' will be 10 trading days. It is advised that the minimum return period should be above one year or at least 250 trading days which are considered as a full trading year.

The main objective of the research study is to identify the most suitable method of computing financial risk in mineral commodities hence various guidelines were adopted for this study. Investors are interested in understanding the probability of losing money in any investment. In order to study the accuracy of these models, various coal and gold mining stocks were tested.

Previous research highlighted that risk associated with VaR and ES models tend to be significant under market stress than in normal market conditions. In order to simulate the financial risk, the share price is simulated against the overall market performance. According to Yamai and Yoshiba (2002), the tail risk is significant when asset losses are infrequent and large. "VaR answers the question: how much can I lose with *x*% probability over a pre-set horizon" (Morgan,1995: pp 6), this is regarded as critical by any investor.

3.2.1. Data inconsistencies

There were some missing data points in the data sets that would affect modelling of the various risk measures. A technique similar to that described by Yamai and Yoshiba (2002) was applied, where all trading days that exist in any data set were added to all remaining data sets where they were non-trading days. The index value on this non-trading day was then set to the same value as on the previous trading day. Table 3.1 shows the process undertaken to insert data points that were missing on 16th June 2015. The change has no significant effect on the outcome of the analysis since this data point has a daily return of zero, which has no effect on the tails of the distribution except for a minor impact on where they begin.

Table 3.1: Data pre and post data adjustment

(a) 16 June 2015 data point missing

Date	High	Low	Close	Volume
10 June 15	9000	8570	8960	
11 June 15	9076	8715	8747	974858
12 June 15	9060	8655	9004	1267583
15 June 15	9014	8854	8950	985637
17 June 15	8969	8655	8720	1108989
18 June 15	8900	8548	8725	707633
19 June 15	8824	8490	8557	904811

(b) Data point for 16 June 2015

Date	High	Low	Close	Volume
10 June 15	9000	8570	8960	1367565
11 June 15	9076	8715	8747	974858
12 June 15	9060	8655	9004	1267583
15 June 15	9014	8854	8950	985637
16 June 15	**9014**	**8854**	**8950**	**0**
17 June 15	8969	8655	8720	1108989
18 June 15	8900	8548	8725	707633
19 June 15	8824	8490	8557	904811

Source: Sharenet (2019)

3.3. Descriptive statistics

Descriptive statistics are useful in describing the basic features of the dataset as they provide simple and meaningful characteristics. Large raw data is often difficult to visualise and to understand the direct interpretation however, descriptive statistics can address this challenge. The descriptive statistics discussed in this study include the standard deviation, mean, skewness and kurtosis.

The standard deviation and mean indicate the volatility of the data. Mean is a good tool to evaluate the performance of a company or portfolio however, it should also be used with other fundamentals and statistical tools to get sufficient insight on the historical and future prospects of investments (Kenton, 2019).

The kurtosis value indicates the distribution of the tail ends. For investors, a high kurtosis of the return distribution implies that the investment may experience occasional extreme returns (either positive or negative).The extreme returns are more than the usual three standard deviations from the mean on either sides that is predicted by the normal distribution of returns (Kenton, 2019). This is often referred to as kurtosis risk. A distribution which has a kurtosis higher than 3 is called leptokurtic, which implies a high peak around the mean and fat tails. Mesokurtic distributions have a kurtosis of 3 matching that of the normal distribution curve, this is also referred to as a bell curve (Statistics Techs, 2017). Kurtosis values that are less than 3 than are referred to as platykurtic, these curves have thinner tails than a normal distribution which results in fewer extreme positive or negative events. Leptokurtic distributions have a relatively high probability of extreme events, whereas the opposite is true for platykurtic distributions (Fernando, 2019). Figure 3.1 provides an indication of how various data sets are described in relation to the kurtosis value.

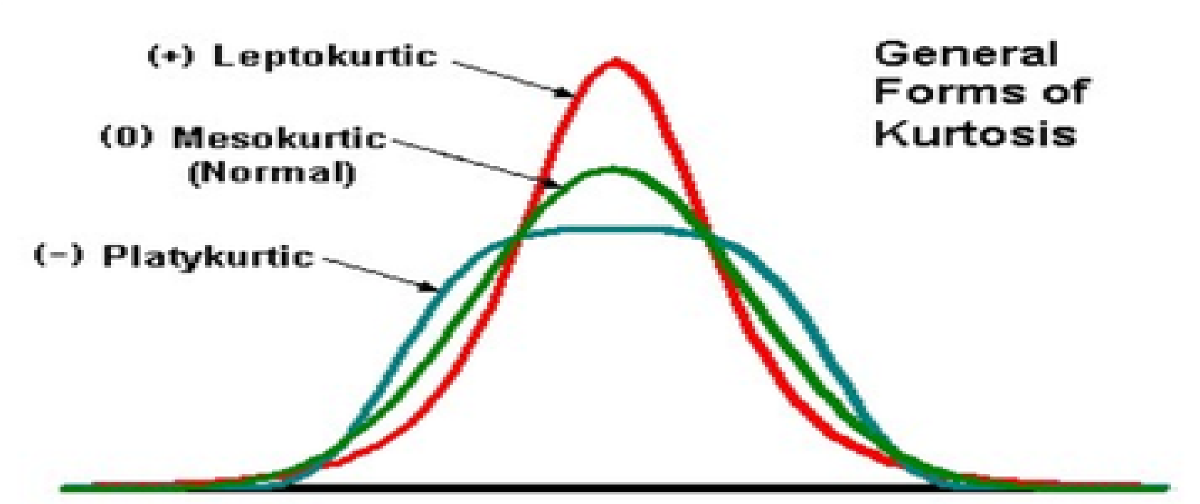


Figure 3.1: Kurtosis distributions

Source: (Statistics Techs, 2017)

3.4. VaR research Methodology

There are three methods of calculating VAR namely; the historical simulation method, variance-covariance method and Monte Carlo Simulation as discussed in Chapter 2. The accuracy of each model is measured by individually backtesting the output of each model and is discussed in Section 3.6.

3.4.1. Historical simulation method

The historical simulation model assumes that the past distribution of returns is a representative of the future performance of the returns (Alexander, 2008). One of the considerations when using the historical simulation model is the fact that, to generate accurate VaR forecasts, the input data set must be large enough to provide adequate predictions of future returns. The historical simulation method assumes the availability of sufficient historical price data, which is often a disadvantage when analysing a horizon that is less than 250 trading days (Kondapaneni, 2005).

The historical simulation method entails counting the total number of observations (*N*) using the count function in Microsoft Excel. The number of observations were multiplied by the corresponding confidence level percentile 90%, 95% and 99%, respectively. The outcomes of the multiplication of the percentiles and the total number of observation *N* determines the “k” value for the data set. The k value was used to identify the corresponding returns using the “SMALL (*array; k*)” function in Microsoft Excel as seen in Table 3.2. The corresponding return was multiplied by the value of the closing share price for the period under review to give the absolute value at risk in cents (ZAC) at a given confidence level.

Table 3.2: Historical simulation formula in Microsoft Excel

=SMALL(H3:H1044;104)

R	S	T	U
Historical Simulation Value at Risk			
N	1042		
	HVaR		**Cents**
10%	104,2	-0,03336	-573,75
5%	52,1	-0,04791	-823,99
1%	10,42	-0,07629	-1312,11

3.4.2. Variance and covariance method

Calculating VaR using variance-covariance method includes determining the expected average returns and standard deviation using the daily returns. These parameters were calculated in Microsoft Excel using the Data Analysis function applying the descriptive statistics function. This method assumes that the returns are normally distributed. Table 3.3 indicates the formula applied in Microsoft Excel.

Table 3.3: Variance and covariance formula in Microsoft Excel

=NORM.INV(10%;L4;L8)

M	N	O	P	Q
		Variance: Covariance Value At Risk		
		Mean	0,0009	
		STD	0,0293	
	Confidence Level	**VaR**		**Cents**
	90%	10%	-0,0366	-630,05
	95%	5%	-0,0473	-813,13
	99%	1%	-0,0672	-1156,55

3.4.3. Monte Carlo Simulation method

Monte Carlo Simulation is like other historical methods except that the data set is generated by a statistical distribution as opposed to historical returns. A probability distribution was selected, and a series of random numbers was generated from the distribution. To simulate returns for the days, random numbers equivalent to the sample size *N* using Microsoft Excel function "INT (rand ())" were generated as seen in Table 3.4. This was repeated several times in order to get the required random numbers or indices (hypothetical distribution). Using the chosen confidence level *c*, VaR was calculated by taking a percentile of the returns and multiplying the percentile value by the latest share price on the available data set.

Table 3.4: Monte Carlo Simulation in Microsoft Excel

I3 =NORM.INV(RAND();L4;L8)

	A	C	D	E	F	G	H	I	V	W	X	Y
1	Date	High	Low	Close	Adj Close	Volume	Returns	Monte Carlo Returns		Monte Carlo Simulation		
2	2015/06/01	8415	8097	8097	6620,68994	200175						
3	2015/06/02	8275	7821	8241	6738,43506	868800	0,01763	0,064036998	N	1042		
4	2015/06/03	8403	8020	8271	6762,96533	1169573	0,00363	0,035247326				
5	2015/06/04	8399	7789	8277	6767,87061	733571	0,00073	-0,011341083		VaR		Cents
6	2015/06/05	8298	8065	8280	6770,32471	1031473	0,00036	-0,031457694	10%	104,200	-0,0383	-658,25
7	2015/06/08	8390	8076	8299	6785,85938	494494	0,00229	-0,003955636	5%	52,100	-0,0472	-811,51
8	2015/06/09	8650	8246	8570	7007,44922	703356	0,03213	-0,032591674	1%	10,420	-0,0716	-1231,75
9	2015/06/10	9000	8570	8960	7326,34033	1367565	0,0445	0,010602607				

3.4.4. Significance levels of VaR models

The Basel Market Risk management framework recommends that VaR is estimated at the 1% and 5% levels of significance. For the purposes of this study, three significant levels will be considered 1%,5% and 10%. Using a higher level of confidence, such as 99.9%, would be more conservative, however a higher confidence level can lead to a false sense of security (Laubsch, 1998). In choosing confidence levels, one should consider worst-case loss amounts that are large enough to be material but occur frequently enough to be observable which is covered when testing different significant levels. In order to validate a VaR model, high confidence levels should not be used to enable the model to observe enough VaR violations that can provide comprehensive information on the model behaviour.

3.5. ES research Methodology

VaR and ES models are based on a single factors process using one tail loss distribution with a given confidence level. Expected Shortfall is derived by calculating the expected average loss conditional to the initial model VaR parameters. Expected Shortfall is the average of all values beyond the threshold of VaR as seen in Table 3.5. For a given confidence level *c*, ES is derived by taking the arithmetic mean of all data points that lie beyond the confidence level of the VaR point. The above can be derived by the following formula in Microsoft Excel.

$$ES_c = AVERAGEIF\,(R_t\!:R_{t+1};\text{"<"}\&VaR_c;R_t\!:R_{t+1}) \qquad (12)$$

Table 3.5: ES simulation in Microsoft Excel

fx =AVERAGEIF(H3:H1044;"<"&T6;H3:H1044)

	U	V	W	X	Y	Z	AA	AB
/alue at Risk		Monte Carlo Simulation				Expected Shortfall		
		N	1042					
	Cents		VaR		Cents		ES	Cents
),03336	-573,75	10%	104,200	-0,0383	-658,25	10%	-0,0524	-901,37
),04791	-823,99	5%	52,100	-0,0472	-811,51	5%	-0,0656	-1128,87
),07629	-1312,11	1%	10,420	-0,0716	-1231,75	1%	-0,1005	-1728,67

3.6. Backtesting Methodology

Backtesting requires the determination of the number of violations from a given data set. A violation is said to occur when the actual loss of the portfolio exceeds the calculated VaR (Chotee, 2014). These violations were determined using the “Count IF” function in Microsoft Excel, this determines the number of observations that exceed the defined VaR value as seen in Table 3.6. The outputs of the violation is used as a basis for determining the accuracy of the model undergoing backtesting. Haas (2001) and Campbell (2005) argued that more than one backtesting technique should always be used to validate the accuracy of a VaR model. The Kupiec test and the Basel traffic light approach were selected as the two testing methods that were applied in this research study as these focus mainly on the number of VaR exceptions. These backtesting methods are used in this research as they are traditional methods and most widely accepted for testing unconditional coverage.

Table 3.6: Determining modelling violation in Microsoft Excel

=COUNTIFS(H673:H922;("<-0,0366"))

N	O	P	Q	R	S	T	U	V	W	X
	Back Testing Variance: Covariance Value At Risk									
	Confidence Level	VaR		N	Expected Exceptions	Realised Exceptions	POF-test LR	Critical Value 95%	Kupiec Test Result	Basel Traffic Light
	90%	10%	-0,0366	250	25	18	2,389	3,84	Accept	Green
	95%	5%	-0,0473	250	13	9	1,138	3,84	Accept	Green
	99%	1%	-0,0672	250	3	3	0,095	3,84	Accept	Green

The Kupiec test assumes that the percentage number of violations must be equal to the VaR significance level multiplied by the number of observations in the holding period. A model which fails this test does not predict VaR accurately for the significance level that was applied, this was the main motivation for applying this method. The test was performed using the realised expectations, x at a confidence level *c,* over N observations. These are substituted into the Equation 9. At a 90% confidence level with 18 realised exceptions and 250 observations /trading days N, the Kupiec test was applied as shown below. The outcomes of the LR_{POF} test would accept the model result of 2,389 as this is below the Chi-squared critical value of 3.84 (i.e. 95% percentile with 1-degree of freedom). The critical value of 3.84 is taken from the Chi-Squared Distribution for the purposes of making a valid conclusion about the model accuracy (Passel, 2016).

$$LR_{POF} = -2ln\,[(1-c)^{(N-x)}c^{x}] \;+\; 2ln[(1-\tfrac{x}{N})^{(N-x)}(\tfrac{x}{N})^{x}\,]$$

$$LR_{POF} = -2ln\,[(1-10\%)^{(250-18)} \times 10\%^{18}] \;+\; 2ln[(1-\frac{18}{250})^{(250-18)} \times (\frac{18}{250})^{18}]$$

$$= 2{,}389$$

The Basel traffic light approach was prescribed by the Basel Committee on Banking Supervision. This is an unconditional backtest because it measures the absolute number of violations over a certain holding period. The cumulative probability of the number of violations observed are classified under one of the three colours: red, yellow and green depending on the number of violations.

3.7. Chapter summary

The approach of this research project as discussed in Chapter 3 is summarised in Figure 3.2. The chapter outlined the sources of data that were considered for the determination of the risk exposure using the different methods. The data was validated was to address inconsistencies that could affect the analysis of risk exposure. The logarithm returns were a key component applied to VaR and ES formulae. A process of validating the outcomes of the risk measures was discussed and the results are presented in Chapter 4.

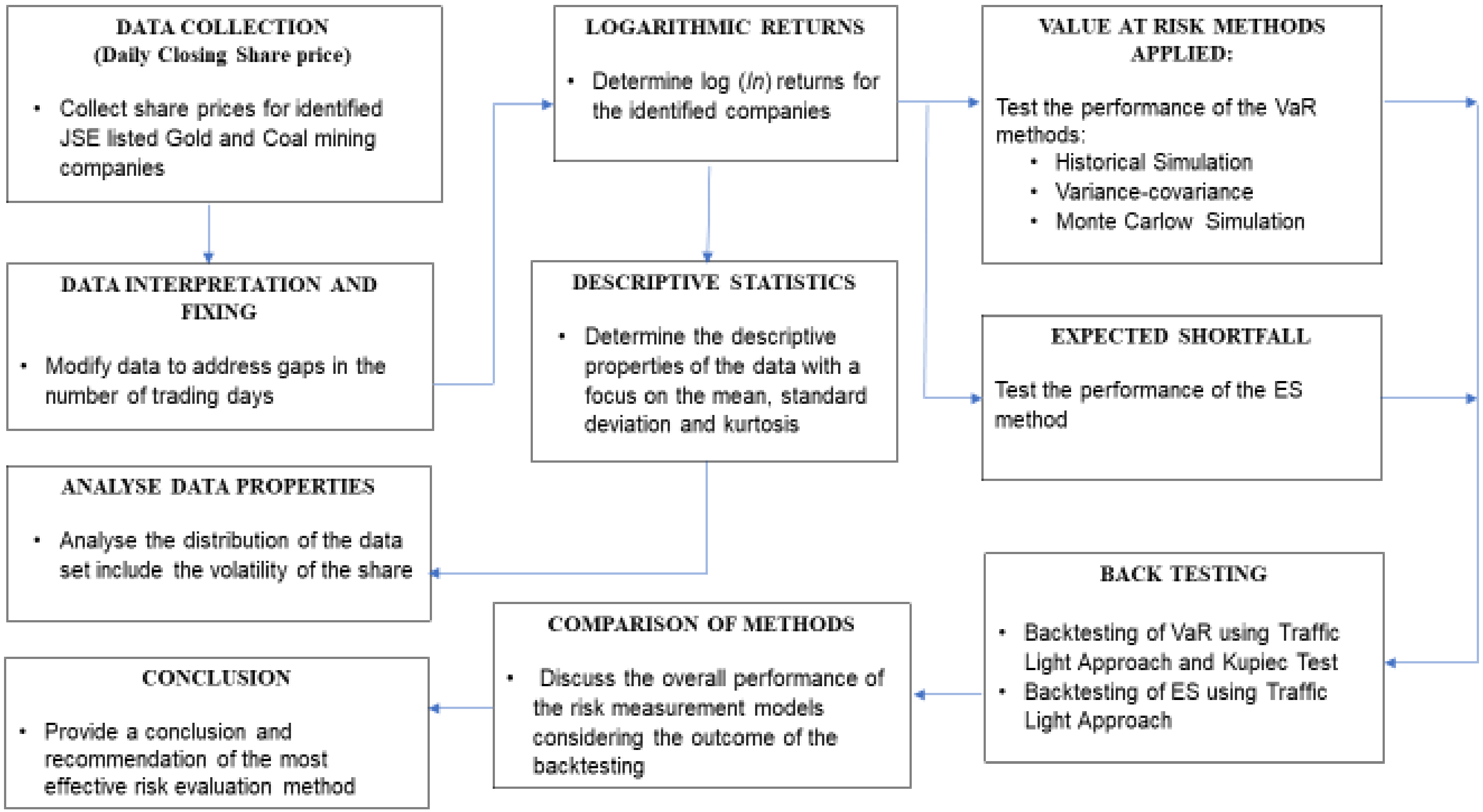


Figure 3.2: Research process flow

4. RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the estimations results of VaR and ES models as derived from the various risk measurement approaches. The data used to calculate the estimations were collected from Sharenet and Yahoo Finance as seen in Appendices 7.1 to 7.5 using the period form 1 June 2015 to 30 June 2019. The period considered is the least sensitive as per Chotee (2014) classification of the various horizon from 2002 to 2012. The recovery period from the Global Financial Crisis is considered to commence from 1 January 2009 as seen in Figure 4.1 that depicts the performance of the JSE All Share index.

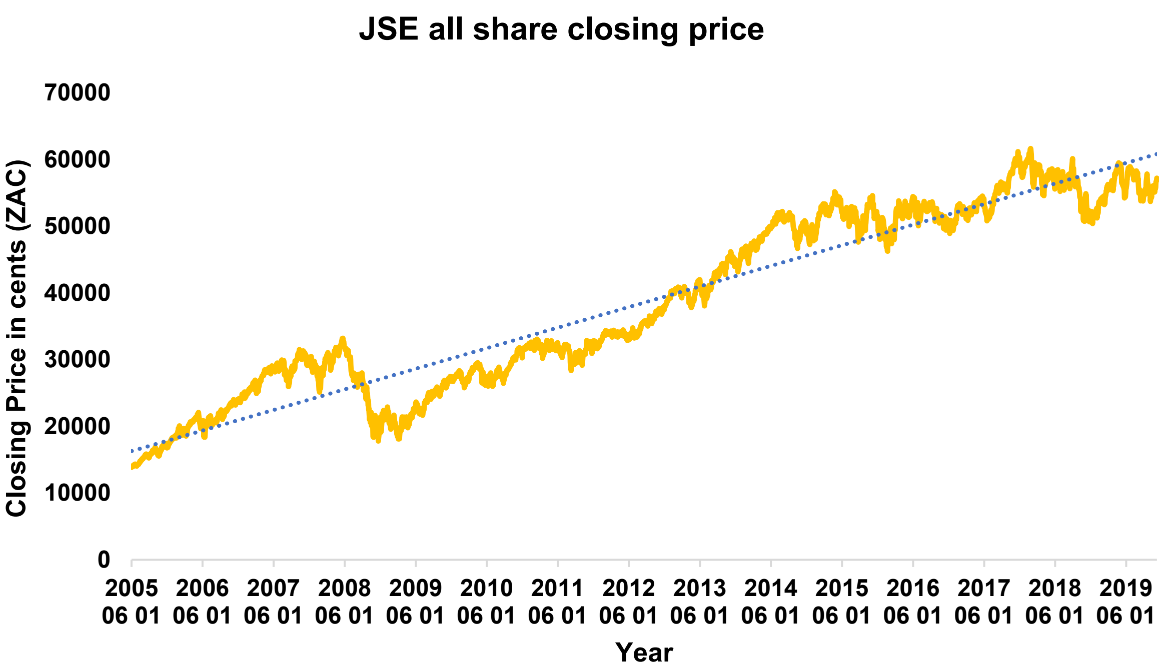
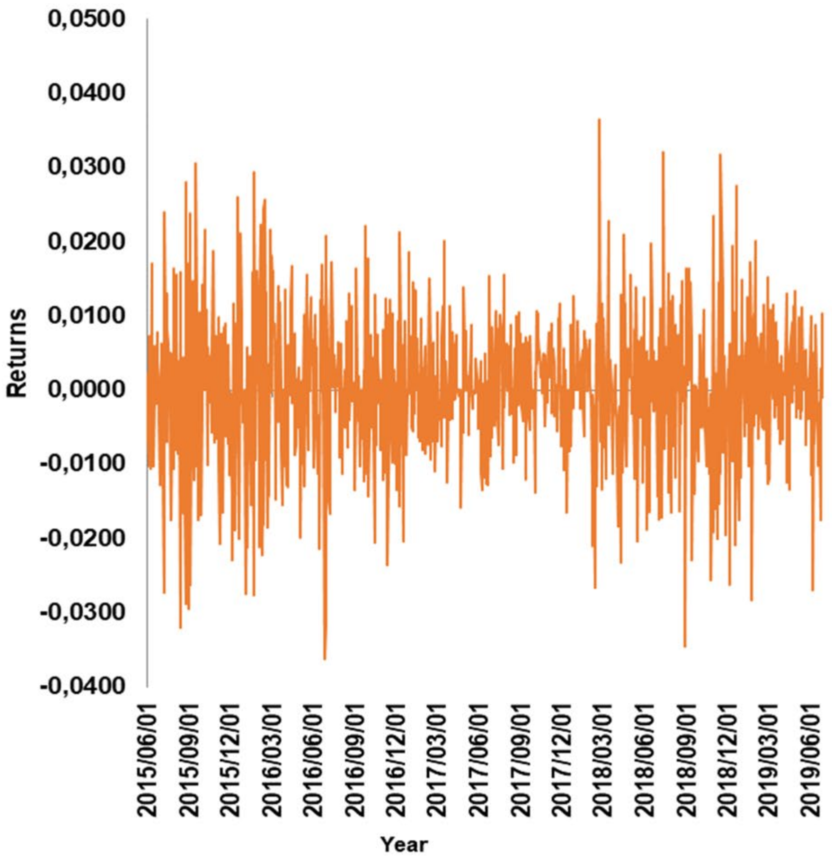


Figure 4.1: JSE All share adjusted closing price: June 2005 -June 2019

Source: (Sharenet, 2019)

There are two notable declines post the Global Financial Crisis in the JSE All Share index in 2016 and 2018. Part of the 2016 decline was due to the decline in share prices of some of the major companies on the JSE. Naspers by 1.94%, PSG fell by 4%, Remgro 8%, British American Tobacco 8%, Steinhoff 2%, Richemont 17%, Aspen 7%, Sasol 7% and Anheuser-Busch In Bev 27% (Hasenfuss, 2016).These are some of the major trading shares in the Johannesburg Stock Exchange hence their performance affected the All Share Index. The decline of the JSE All Share Index was further impacted by the Brexit decision that affected popular United Kingdom (UK) aligned stocks. Companies analysed in this study depict similar trends however, this does not have a significant impact of the risk measure as the volatility was over a short period.

According to Financial News 24 (2018), the year 2018 was a challenging year for the JSE All Share Index as 15.18% was shed by November 2018. Analysts argued that the JSE's decline is related to uncertainty about land expropriation without compensation pronounced by the South African government, national elections and the general downward trend of emerging economies following the economic crises in Turkey and Argentina (Financial News 24, 2018). The returns of the JSE All Share Index is depicted in Figure 4.2 and further supported by the descriptive statistics. The volatility experienced by the market in 2018 can be seen on the return distribution graph.



JSE All Share Descriptive Statistics	
Mean	0,00005242
Standard Error	0,00029634
Median	0,00000000
Mode	0,00000000
Standard Deviation	0,00956593
Sample Variance	0,00009151
Kurtosis	1,15956664
Skewness	-0,15922165
Range	0,07271079
Minimum	-0,03621479
Maximum	0,03649600
Sum	0,05462134
Count	1042

Figure 4.2: Distribution of returns for JSE all share returns: June 2015-June 2019

Some of the top performing stocks such as Mediclinic, Tiger Brands, British American Tobacco and Aspen all fell by more than 40% in the year to end November 2018. MTN fell by 33%, and Naspers, Richemont and Anheuser-Busch InBev by 17%, 19% and 22%. Around 65% of shares on the JSE have fell by over 20%, meeting the definition of being in a “bear market” (Overberg Asset Management, 2018).

The standard deviation of the returns for the JSE All Share Index is higher than the mean value while the mean value is closer to zero. When the mean is closer to zero and the standard deviation is higher than the mean, the returns are considered as very volatile (Almli & Rege, 2011). The Kurtosis value of the daily returns is less than 3 and the skewness of the logarithmic returns is less than zero. The data set is considered as platykurtic due to the 1.15 kurtosis value. This implies that the data does not follow a normal distribution as the distribution is short and the tails are thinner than normal.

4.2 Descriptive statistics for coal mining companies

The descriptive statistics of the daily logarithmic returns for the coal companies under review from 1 June 2015 to 28 June 2019 for this study are presented in Table 4.1. The standard deviation of the returns for the two companies (Exxaro and Sasol) are higher than mean value while the mean value is closer to zero. The relationship between the mean and standard deviation indicates that the coal companies’ shares are volatile particularly Exxaro with a standard deviation of 2.93%. Sasol has a standard deviation of 1.99%. Almli and Rege (2011) indicated that the common standard deviation for stocks and stock indices ranges between 0.7 % and 2% for the daily logarithmic returns.

Table 4.1: Coal Companies Descriptive Statistics

Coal Companies	***Exxaro***	***Sasol***
Mean	0.09%	-0.01%
Standard Error	0.09%	0.06%
Median	0.09%	0.00%
Mode	0.00%	0.00%
Standard Deviation	2.93%	1.99%
Sample Variance	0.0009	0.0004
Kurtosis	3.0430	4.2503
Skewness	0.1064	-0.4284
Range	29.82%	22.07%
Minimum	-12.61%	-13.92%
Maximum	17.21%	8.16%
Sum	95.47%	-6.49%
Count	1042	1042

Kurtosis is a measure of the combined weight of the tails relative to the rest of the distribution. The Kurtosis values of the daily returns for the coal companies are greater than 3 and the skewness of the logarithmic returns is greater than zero. This implies that the data does not follow a normal distribution. The peak of the returns is higher than the normal distribution, this type of distribution is referred to as leptokurtic. Figure 4.3 depicts the distribution of the returns and it is observed that the tails are fatter. Outliers stretch the horizontal axis of the graph, which makes the bulk of the data appear in a narrow vertical range, thereby giving the “skinniness” of a leptokurtic distribution.

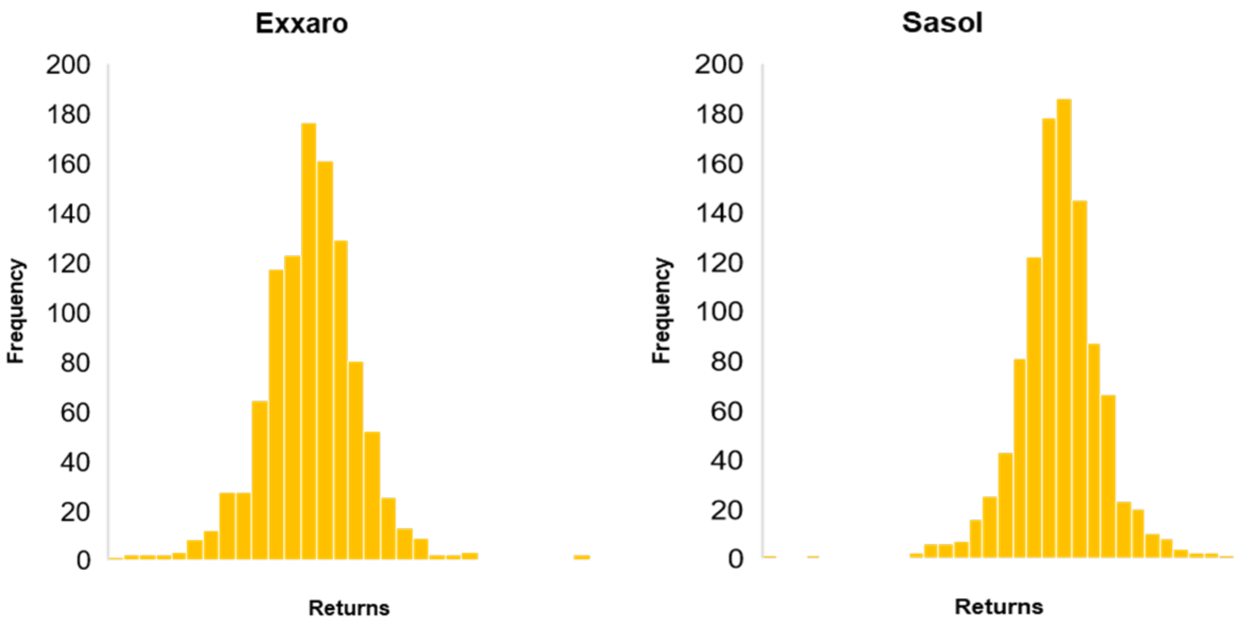


Figure 4.3: Return distribution of coal companies

4.3 Descriptive statistics for gold mining companies

The descriptive statistics of the daily logarithmic returns for the gold companies under review from 1 June 2015 to 28 June 2019 are presented in Table 4.2. The standard deviation and mean of the returns for gold companies (Anglo Gold Ashanti, Gold Fields and Harmony) are indicating that the data is volatile as the values are greater than 3% and 0.5% respectively. The volatility is due to the proximity of the mean to zero and the high standard deviation that lies outside the range of 0,7% and 2% as identified by Almli and Rege (2011).

Table 4.2: Gold Companies Descriptive Statistics

Coal Companies	Anglo Gold Ashanti	Gold Fields Limited	Harmony
Mean	0.08%	0.06%	0.06%
Standard Error	0.09%	0.10%	0.12%
Median	0.00%	0.00%	0.00%
Mode	0.00%	0.00%	0.00%
Standard Deviation	3.01%	3.23%	3.74%
Sample Variance	0.0009	0.0010	0.0014
Kurtosis	1.6905	3.4861	2.4775
Skewness	0.2888	0.0299	0.1873
Range	23.33%	31.70%	36.34%
Minimum	-11.20%	-16.03%	-17.71%
Maximum	12.12%	15.67%	18.63%
Sum	79.94%	66.56%	61.41%
Count	1042	1042	1042

The kurtosis values of the daily returns range between 1.6-3.4, this means that some of the data are platykurtic due to the kurtosis values that are less than 3 while others are leptokurtic as the value is above 3. Platykurtic distributions are thinner than the normal distribution and the tails of the data is shorter than the normal distribution. Kurtosis value for a normal distribution is 3 and is referred to as mesokurtic. Figure 4.4 depicts the distribution of the returns of the gold companies highlighting that Anglo Gold Ashanti and Harmony are platykurtic and Gold Fields Limited has a leptokurtic distribution.

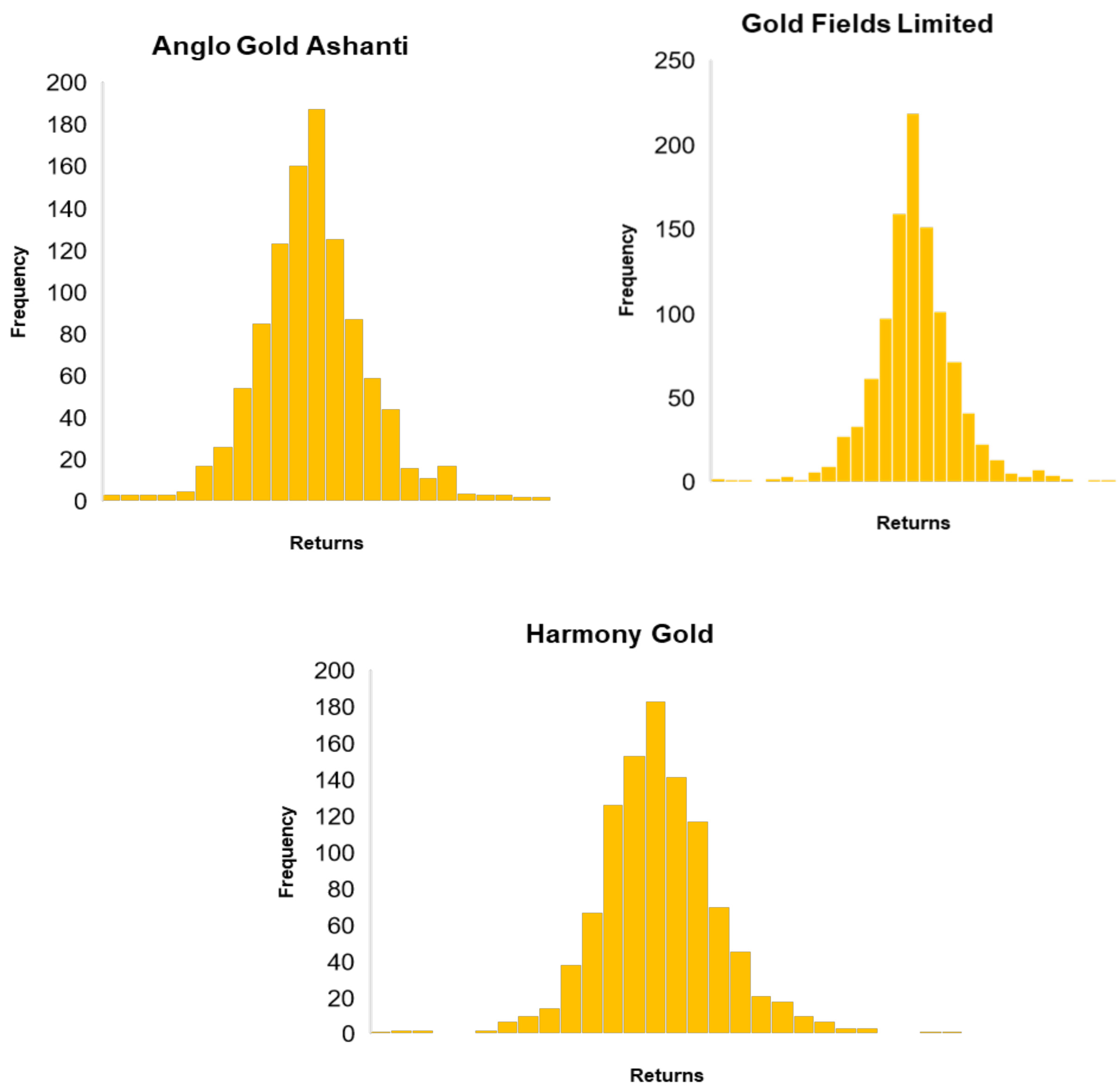


Figure 4.4: Return distribution of goal companies

4.4 Coal mining companies results

4.4.1. Exxaro Resources Limited

The adjusted closing share price for Exxaro is depicted in Figure 4.5. The share price of the company has grown significantly over the period under review from R66,20 on the 1st of June 2015 to as high as R171,99 on 30th June 2019. The company initially listed on the JSE with a share price of R102,5 and dropped to approximately R53,5 in October 2008, during the Global Financial Crisis.

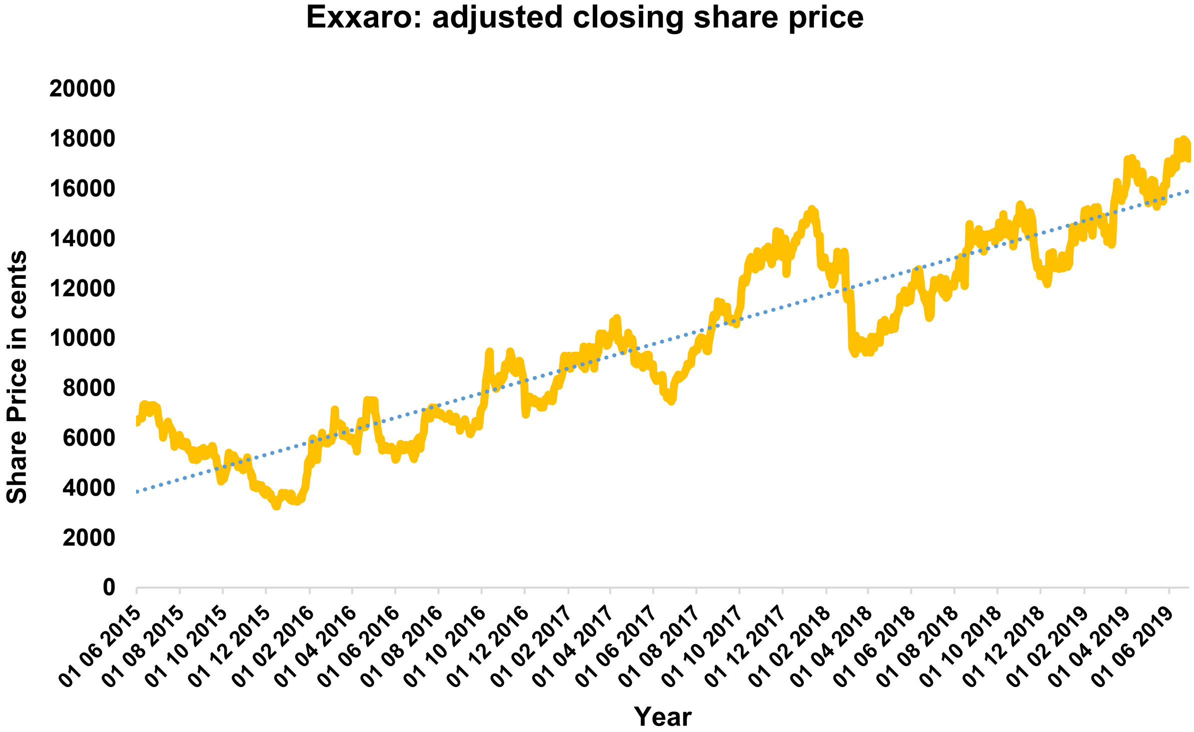


Figure 4.5: Exxaro adjusted closing price: June 2015-June 2019

Source: (Sharenet, 2019)

The share price has more than doubled over the last four years however, several price dips are observed towards the end of 2015 and the beginning of 2018 as seen in Figure 4.5. The lowest reported share prices was R32,55 and this was recorded towards the end of 2015 and the beginning of 2016. The observed decline in 2015/2016 followed the same trend as the JSE All Share Index. Key strategic decisions undertaken by Exxaro in 2016 such as the disposal of non-core assets mainly Inyanda and Mayoko iron ore projects contributed to the improvement of the companies share performance (Exxaro, 2016). The company highlighted that the strategy was to ensure that it retains commodities that can withstand a low commodity price environment (Exxaro, 2016).

Following years of weakness due to weather disruptions, above average seasonal supply and demand of coal and most notably the 276-operating days per annum policy implemented by the Chinese government, coal markets showed some improvement during the second half of 2016. This managed to contribute to a positive performance of the company as thermal and hard coking coal prices surged (Exxaro, 2016). The surge in commodity prices allowed commodity producing countries like South Africa, Russian and Brazil to have a positive Gross Domestic Product (GPD) as a result of the commodity sales (Exxaro, 2016).

The volatility observed in Figure 4.5 is evident in the return distribution presented in Figure 4.6 with March 2018 being the period with the most extreme fluctuations. Negative returns are the main concern when analysing the financial performance of a company because investors are more concerned with managing losses and maximising returns. The volatility in March can be attributed to the warning issued by Exxaro to its shareholders that its basic headline earning per share for 2017 were expected to be 20% of the previous year. The headline earning per share for the year to end December 2017 would be between 24c and 29c, this was a sharp declined from the previous year at R13,02 (Johwa, 2018).

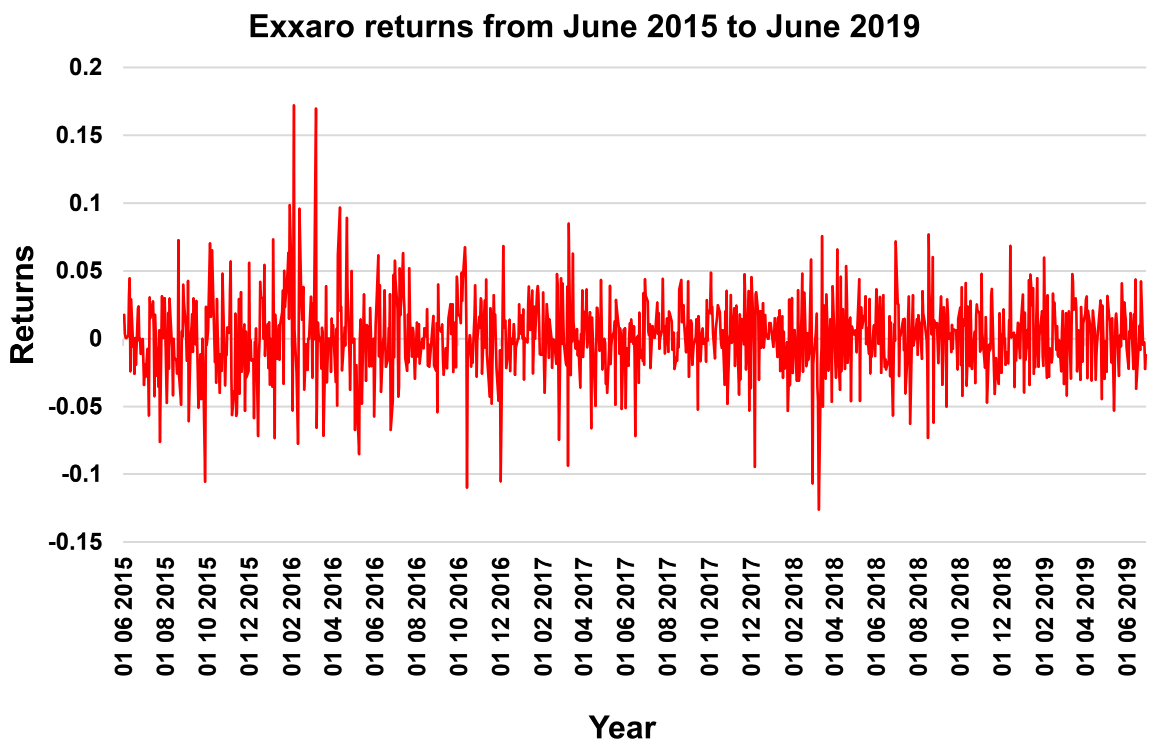


Figure 4.6: Distribution of returns for Exxaro: June 2015-June 2019

The results presented in Table 4.3 indicate the performance of VaR and ES models for Exxaro at different confidence levels over the period under review. The outcomes of the ES model values are higher than the VaR methods. These results are in line with literature as the ES value should indicate the worst-case scenario which is higher than values derived from VaR methods.

***Table 4.3:* Exxaro Value at Risk and Expected Shortfall results**

	Variance-Covariance Value at Risk			Historical Simulation Value at Risk			Monte Carlo Simulation			Expected Shortfall	
	Mean	0,0009		Number of observations :1042			Number of observations :1042				
	STD	0,0293									
Confidence Level	**VaR**		**Cents**	**HVaR**		**Cents**	**VaR**		**Cents**	**ES**	**Cents**
90%	10%	-0,0366	-630,05	104,2	-0,03336	-573,75	104,2	-0,0355	-610,14	-0,0524	-901,37
95%	5%	-0,0473	-813,13	52,1	-0,04791	-823,99	52,1	-0,0469	-807,31	-0,0656	-1128,87
99%	1%	-0,0672	-1156,55	10,42	-0,07629	-1312,11	10,42	-0,0685	-1177,90	-0,1005	-1728,67

At higher confidence levels of 99%, the VaR risk models give possible losses that range between R11,57 to R13,12. The VaR results at the 99% confidence level give outputs that are closer to ES results at 95% confidence level of R11,28. The results from the variance covariance models and Monte Carlo Simulation are not far apart from each other when compared to historical simulation. At 95% confidence, the variance covariance method gives a possible loss off R8,13 while Monte Carlo give a possible loss of R8,07. These outcomes are far from the R8,24 yielded by the historical method. The ES model performed as expected given that the outcomes at various confidence levels are higher than the all the VaR results.

The Historical simulation values at the 95% and 99% confidence levels are higher values than the variance covariance models because the actual price changes do not perfectly follow a normal distribution, this is also supported by Exxaro's kurtosis of 3.0430. The data is asymmetrical (lean to the left) with higher probability of negative values given the skewness of 0.1064.

Table 4.4 presents the outcomes of the backtesting of both VaR and ES models for Exxaro. The results indicate that the all models pass the various requirements of the likelihood ratio test and the traffic light test. The LR test ratio for Exxaro ranges from 0,021 to 2,389. The realised exceptions across the various VaR models fall within the expected exception ranges at different confidence levels. For Exxaro, both the VaR and ES models pass the backtesting requirements however, there is an average gap of R3,00 between ES and VaR values. The underestimation of VaR models in Exxaro renders the models ineffective. ES would be more suitable in this case.

Table 4.4: Exxaro backtesting output

Variance-Covariance Value at Risk									
Confidence Level	**VaR**		**Number of observation**	**Expected Exceptions**	**Realised Exceptions**	**POF-test LR**	**Critical Value 95%**	**Kupiec Test Result**	**Basel Traffic Light**
90%	10%	-0,0366	250	25	18	2,389	3,84	Accept	Green
95%	5%	-0,0473	250	13	9	1,138	3,84	Accept	Green
99%	1%	-0,0672	250	3	3	0,095	3,84	Accept	Green
Historical Simulation Value at Risk									
90%	10%	-0,0334	250	25	24	0,0449	3,84	Accept	Green
95%	5%	-0,0479	250	13	9	1,1380	3,84	Accept	Green
99%	1%	-0,0763	250	3	2	0,1080	3,84	Accept	Green
Monte Carlo Simulation									
90%	10%	-0,0381	250	25	24	0,386	3,84	Accept	Green
95%	5%	-0,0481	250	13	11	0,021	3,84	Accept	Green
99%	1%	-0,0672	250	3	1	1,956	3,84	Accept	Green
Expected Shortfall									
Confidence Level	**ES**		**N**	**Expected Exceptions**	**Realised Exceptions**	**POF-test LR**	**Critical Value 95%**	**Kupiec Test Result**	**Basel Traffic Light**
99%	1%	-0,1005	250	3	2	N/A	3,84	N/A	Green

4.4.2. Sasol Limited

The overall share price for Sasol has grown gradually over the period under review. Figure 4.7 indicates the overall trend of the share price highlighting the declining price since October 2018 from R554,84 to as low as R350,21 in June 2019. Economists have attributed the share price decline to the strengthening rand and declining oil price. The share performance of Sasol often follows the same trend as the Brent crude price however, the company indicated that this would change in the future as their investment in Lake Charles Chemical Project yields results depending on prices of chemicals (Sasol, 2019).

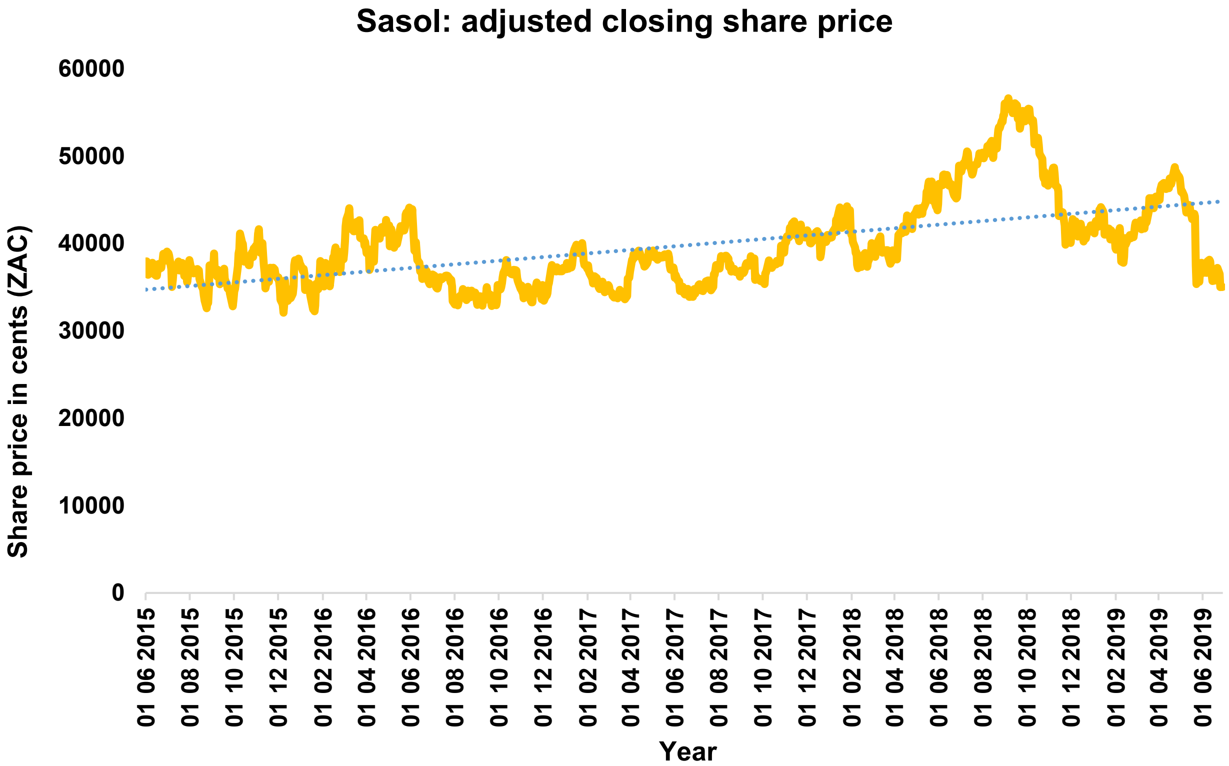


Figure 4.7: Sasol adjusted closing price: June 2015-June 2019

Source (Sharenet, 2019)

Sasol's share price has dropped by as much as 37.12% in 2019 (Maeko, 2019). The drop-in share price can be observed from October 2018 as seen in Figure 4.7 and the trend continues in 2016. Unlike Exxaro, the decline in share price of Sasol is arguably self-inflicted as the company indicated that poor project management on their Lake Charles Chemical Project was the biggest drive in share price decline in 2019 (Sasol, 2019).

Sasol experienced significant volatility in June 2016 and June 2019 as seen in Figure 4.8 despite a standard deviation of 1,99%. These two periods yield the most notable negative returns that is above -0,1. The volatility in June 2016 was due to a 30% profit decline as the company managed lower fuel prices and experienced a R11 billion impairment on its share of a shale gas asset in Canada (Financial News 24, 2016). The headline earnings were forecasted to decrease by 10-30% in the financial year ending June 2016. The headline earning per share dropped from R49,80 to R41 from 2015 to 2016.

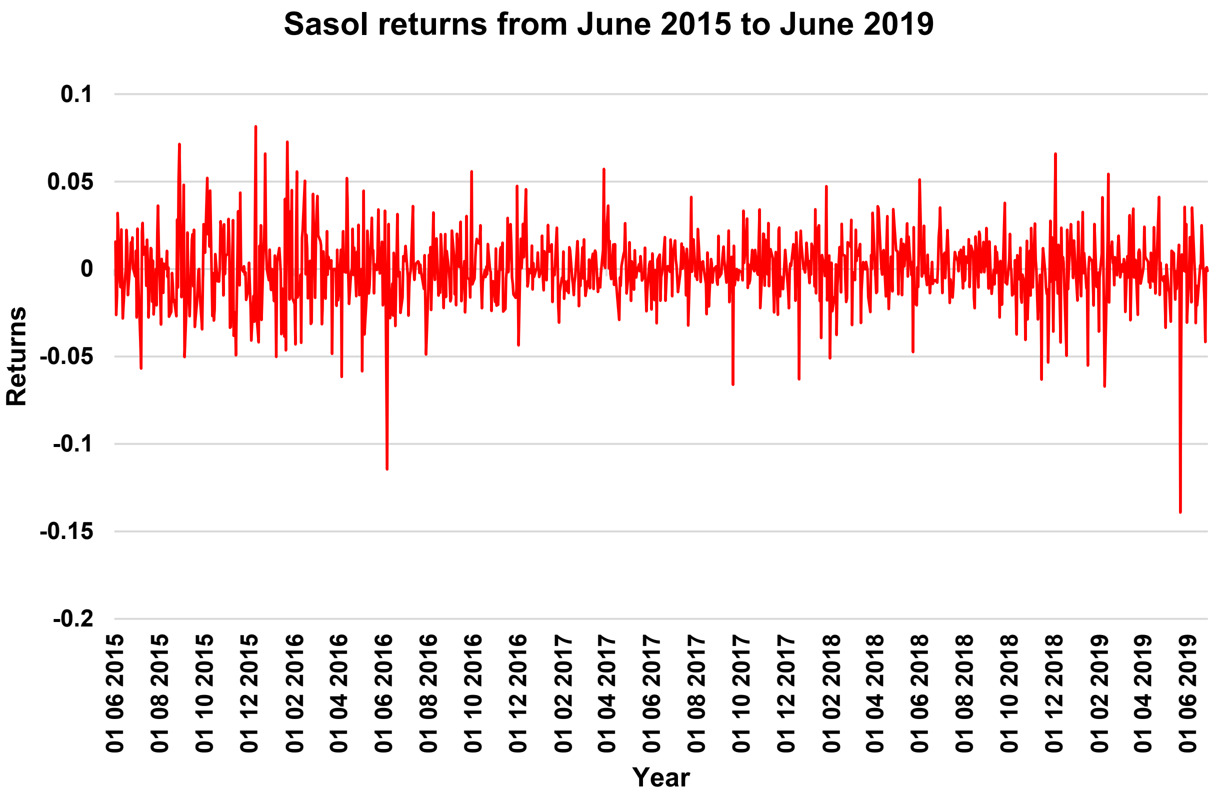


Figure 4.8: Distribution of returns for Sasol: June 2015-June 2019

Tables 4.5 and 4.6 indicate the outcomes of the VaR models, ES model and backtesting results at different confidence levels for Sasol. The possible loss from the profile ranges between R7,84 to R19,93 when using VaR methods, these values are less than the worst-case scenario of R 23,93 derived from the ES model. At a 99% confidence level, the historical simulation predicts higher possible loss of R19,93 in comparison to the other two VaR models.

Table 4.5: Sasol Value at Risk and Expected Shortfall results

	Variance: Covariance Value at Risk			Historical Simulation Value at Risk			Monte Carlo Simulation			Expected Shortfall	
	Mean	-0,0001		Number of observations :1042			Number of observations :1042				
	STD	0,0199									
Confidence Level	VaR		Cents	HVaR		Cents	VaR		Cents	ES	Cents
90%	10%	-0,0255	-894,235	104,2	-0,0224	-784,39	104,200	-0,0240	-840,872	-0,0367	-1285,26
95%	5%	-0,0328	-1147,12	52,1	-0,0309	-1082,27	52,100	-0,0306	-1070,501	-0,04712	-1650,36
99%	1%	-0,0463	-1621,49	10,42	-0,0569	-1993,74	10,420	-0,0438	-1533,045	-0,07691	-2693,41

The outcomes of the backtesting results indicate that there are accuracy problems with the VaR models when testing Sasol's performance at various confidence levels particularly at 99% confidence level. The outcomes of Sasol's LR test ratio lies between 0,0213 and 9,7308 at different confidence levels and VaR methods. Table 4.6 indicates that most of the VaR models fail the likelihood ratio test at a 99% confidence level and the traffic light test indicates possible risks as most of the test results lie in the yellow code. Yellow zone consists of exceptions from five to nine. These outcomes could be produced by both accurate and inaccurate models with relatively high probability, even though they are more likely for inaccurate models. Backtesting results in the yellow zone generally cause an increase in the multiplication factor, depending on the number of exceptions. The failure of the VaR models indicates that the applied method will failure to provide accurate risk measure when the data has extreme losses.

The ES models pass the traffic light test at 99% as the realised exception of 0 falls within the green zone. The absolute losses of R12,85, R16,50 and R26,93 as per the ES modelling provide a less conservative number to monitor the possible losses as opposed to the VaR outputs. The ES model performed better when applied to Sasol based on the backtesting results.

Table 4.6: Sasol backtesting output

Confidence Level	VaR		N	Expected Exceptions	Realised Exceptions	POF-test LR	Critical Value 95%	Kupiec Test Result	Basel Traffic Light
Variance-Covariance Value at Risk									
90%	10%	-0,0255	250	25	16	4,074	3,84	Reject	Green
95%	5%	-0,0328	250	13	11	0,1970	3,84	Accept	Green
99%	1%	-0,0463	250	3	5	1,9560	3,84	Accept	Yellow
Historical Simulation Value at Risk									
90%	10%	-0,0224	250	25	20	0,0449	3,84	Accept	Green
95%	5%	-0,0309	250	13	12	0,0213	3,84	Accept	Green
99%	1%	-0,0569	250	3	1	1,1760	3,84	Accept	Green
Monte Carlo Simulation									
90%	10%	-0,0243	250	25	41	9,7308	3,84	Reject	Yellow
95%	5%	-0,0329	250	13	18	2,2550	3,84	Accept	Yellow
99%	1%	-0,0451	250	3	6	3,5550	3,84	Reject	Yellow
Expected Shortfall									
Confidence Level	**ES**		**N**	**Expected Exceptions**	**Realised Exceptions**	**POF-test LR**	**Critical Value 95%**	**Kupiec Test Result**	**Basel Traffic Light**
99%	1%	-0,0769	250	3	0	N/A	3,84	N/A	Green

4.5 Gold mining companies results

4.5.1. Anglo Gold Ashanti

Gold producers experienced significant improvements in the gold price towards the end of 2015 and throughout 2016, the prices peaked to US$1,375.25/oz. This can be seen in the share price of Anglo Gold Ashanti in Figure 4.9. The share price during the period under review went as high as R310,75 in mid-2016. The company reported that 2016 was an eventful year and various global events helped to drive the gold price from the sharp sell-off in Chinese equities to a pick-up in friction between Saudi Arabia and Iran (Anglo Gold Ashanti, 2016).

The most influential factor that contributed to the gold price was the United States (US) dollar. The absence of any increase in US interest rates during the first half of the year in 2016 allowed gold to rally however, as the US economy started to improve towards the end of the year and the likelihood of a rate hike increasing in the fourth quarter, the gold price started to decline (Anglo Gold Ashanti, 2016).

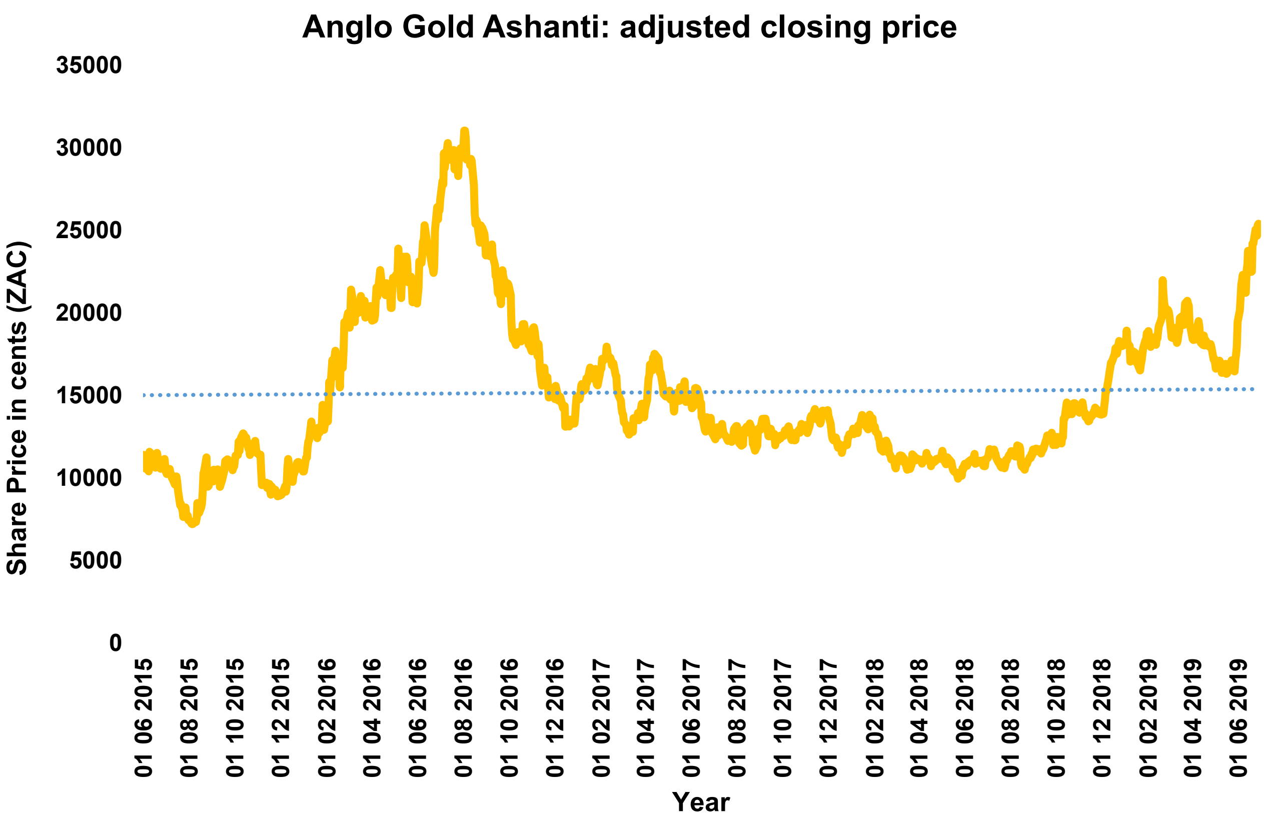


Figure 4.9: Anglo Gold Ashanti adjusted closing price: June 2015-June 2019

Source: Sharenet (2019)

The 2016 revival of Exchange Traded Funds (ETF) demand created an increase in the number of investors buying into gold therefore driving the price of gold higher. In addition to the global events previously discussed, continued sluggish economic growth across the globe, despite the attempts by Central Banks to reflate economies made gold the preferred safe haven asset (Anglo Gold Ashanti, 2016). The price for gold declined towards the end of 2016 forcing Anglo Gold Ashanti's share price to stabilise in 2017.

As seen in Figure 4.10, Anglo Gold Ashanti experienced some fluctuations between 2015 and 2019. It is evident that the fluctuations presented by the graph are clustered and if the volatility is higher or lower at a certain period, the opposite trend will be observed in the following period. This phenomenon is called volatility clustering (Noshkov and Demirtas, 2017). Volatility clustering is a principle that explains an aggregation of high (low) volatilities in time. Fluctuation that stand out can be seen between 2015 and 2016 performance as the returns exceed -0,1 which reflects a high concentration of negative returns. The company reported losses of $127 million in the last three months ending June 2015, compared to $89 million over the same periods in the previous year. Some of the 2016 fluctuations to the gold markets and financial markets in general were attributed to the election of Donald Trump as the president of the United States of America (Anglo Gold Ashanti, 2016).

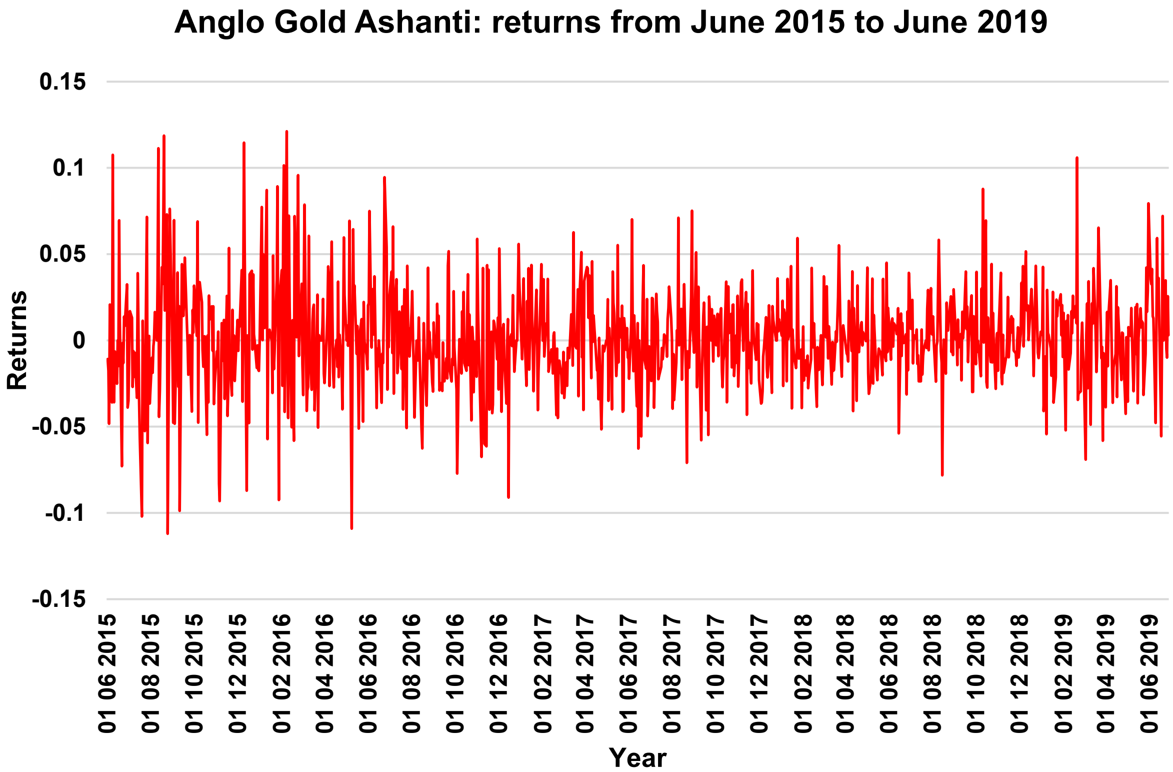


Figure 4.10: Anglo Gold Ashanti return distribution

The outcomes of the VaR and ES models are presented in Table 4.7 based on the returns of Anglo Gold Ashanti. At lower confidence levels of 90% and 95%, the historical simulation method gives the lowest predictions of possible losses ranging between R8,90 and R11,33 in comparison to the other VaR models with results ranging between R9,59 and R12,37. The results from the variance-covariance model and Monte Carlo Simulation are not far apart from each other when compared to historical simulation. The outcomes of Monte Carlo Simulation and variance-covariance model ranges between R9,56 and R17,58 while the historical simulation model estimates losses that ranges between R8,90 and R19,86. The similarity between the variance-covariance and Monte Carlo values arises due to the reliance on the same mean and standard deviation for the simulation of future values.

Results from the ES model at different confidence levels are higher than the values derived from the VaR models. The expected losses from the ES model range between R12,97 and R24,52.

Table 4.7: Anglo Gold Ashanti Value at Risk and Expected Shortfall results

	Variance: Covariance Value at Risk			Historical Simulation Value at Risk			Monte Carlo Simulation			Expected Shortfall	
	Mean	0,00077		Number of observations :1042			Number of observations :1042				
	STD	0,03008									
Confidence Level	VaR		Cents	HVaR		Cents	VaR		Cents	ES	Cents
90%	10%	-0,0378	-959,76	104,2	-0,0350	-890,24	104,2	-0,037	-951,51	-0,0511	-1297,80
95%	5%	-0,0487	-1237,4	52,1	-0,0446	-1133,70	52,1	-0,048	-1231,26	-0,0631	-1602,10
99%	1%	-0,0692	-1758,1	10,42	-0,0782	-1986,11	10,42	-0,066	-1688,31	-0,0965	-2452,24

Table 4.8 presents the various outcomes of the backtesting results for Anglo Gold Ashanti. The outcomes of the Kupiec Test rejects the variance covariance method and the historical simulation at a 90% and 95% confidence however, these results are accepted by the Basel traffic light test. The LR ratio of 22,436 for Anglo Gold Ashanti is high in comparison to coal companies with the highest value at 9,7308. The outcomes of the likelihood test ratio indicated that ES is a better model in the analysis of Anglo Gold Ashanti.

Table 4.8: Anglo Gold Ashanti backtesting output

Confidence Level	VaR		N	Expected Exceptions	Realised Exceptions	POF-test LR	Critical Value 95%	Kupiec Test Result	Basel Traffic Light
Variance-Covariance Value at Risk									
90%	10%	-0,0366	250	25	6	22,436	3,84	Reject	Green
95%	5%	-0,0473	250	13	2	14,127	3,84	Reject	Green
99%	1%	-0,0672	250	3	1	1,176	3,84	Accept	Green
Historical Simulation Value at Risk									
90%	10%	-0,0350	250	25	6	22,436	3,84	Reject	Green
95%	5%	-0,0446	250	13	2	14,127	3,84	Reject	Green
99%	1%	-0,0782	250	3	0		3,84	N/A	Green
Monte Carlo Simulation									
90%	0,1	-0,0373	250	25	24	0,0000	3,84	Accept	Green
95%	0,05	-0,0492	250	13	12	1,1380	3,84	Accept	Green
99%	0,01	-0,0703	250	3	2	1,1760	3,84	Accept	Green
Expected Shortfall									
Confidence Level	**ES**		**N**	**Expected Exceptions**	**Realised Exceptions**	**POF-test LR**	**Critical Value 95%**	**Kupiec Test Result**	**Basel Traffic Light**
99%	1%	-0,0965	250	3	0	N/A	3,84	N/A	Green

4.5.2. Gold Fields Limited

Gold Fields experienced trends that are similar to other gold producers in the 3rd quarter of 2016 with a rising share price as seen in Figure 4.11. The share price peaked to R86,15 in August 2016 following the increase in the gold price. It was highlighted that the gold price increased by almost US$ 100/oz following British Exit (Brexit) of the European Union which was US$ 250/oz higher than the financial planning price used by the company for the 2016 financial year (Gold Fields, 2016). Significant improvements in the headline earnings and normalised earnings were reported by the company when comparing the first half of 2016 against 2015.

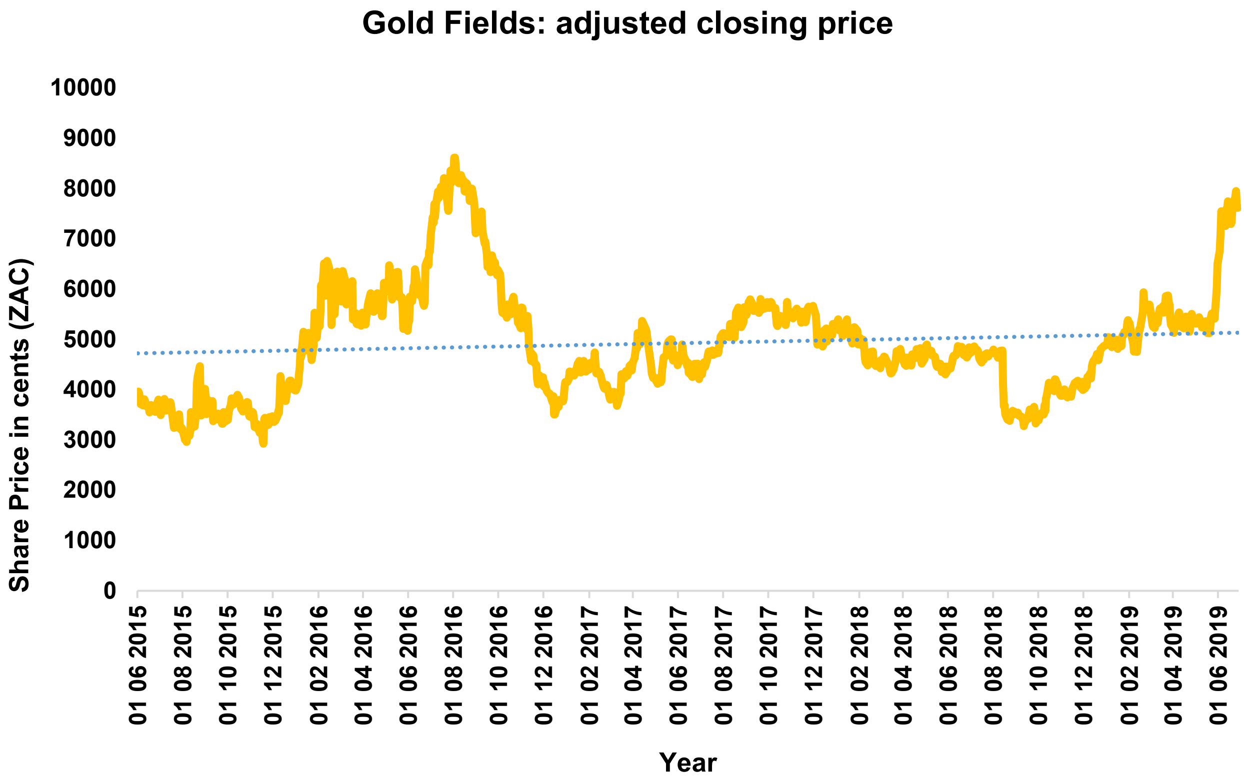


Figure 4.11: Gold Fields Limited adjusted closing price: June 2015-June 2019

Source: Sharenet (2019)

Headline earnings for the first of half of 2016 was US$ 124 million (US$ 0.16/ share), compared to US$ 5 million (US$ 0.01/share) reported in the first half of the 2015 financial year (Gold Fields, 2016). The normalised earnings for the period was US$ 103 million (US$ 0.13/share) compared to US$ 8 million (US$ 0.01/share) reported for the first half of 2015 (Gold Fields, 2016). Good cost control measures that resulted in lower net operating costs and the increase in the dollar price of gold were highlighted as the main contributors to the overall increases in earnings (Gold Fields, 2016).

The return distribution presented in Figure 4.12 for Gold Fields indicates that the volatility experienced in August 2018 is similar to the experience of Anglo Gold Ashanti during the same period. The volatility encountered in August 2018 was due to the interim net loss of $ 369 million reported by the company from the unprofitable South African operations and the restructuring of costs in Ghana (Seccombe, 2018). The standard deviation of 3,74% is the highest of the three gold companies under review.

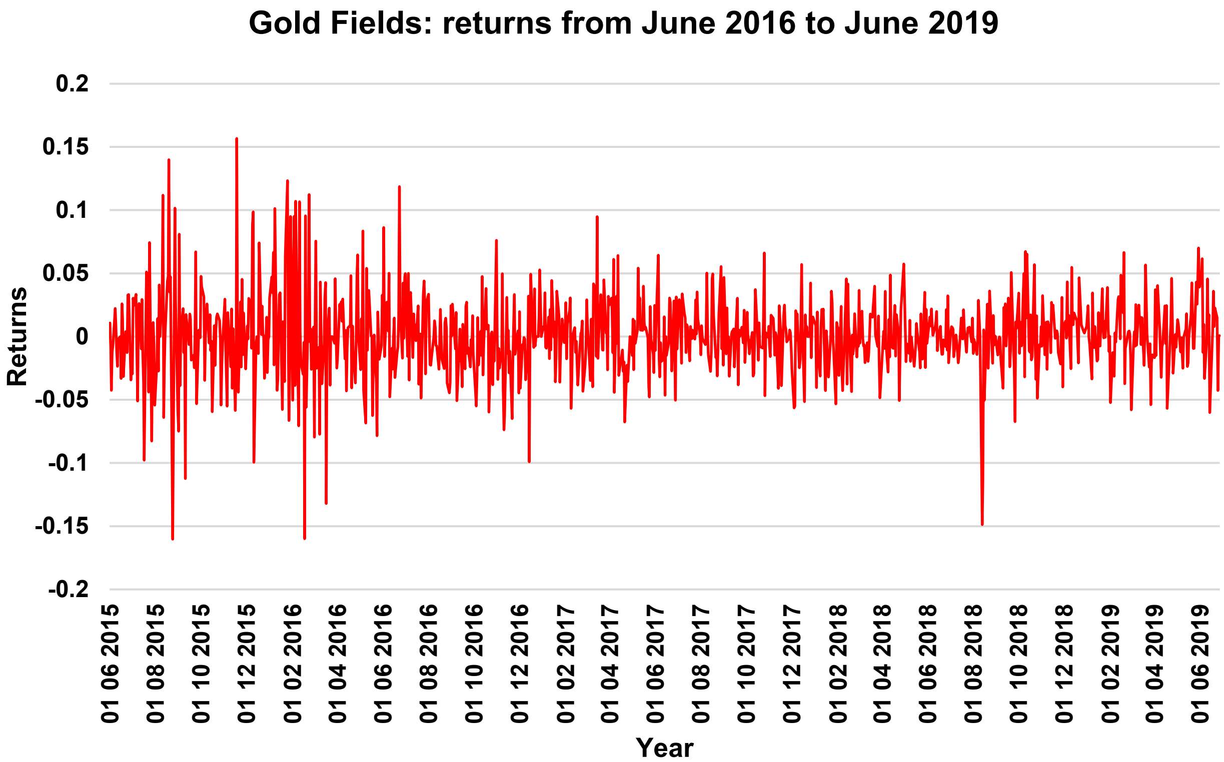


Figure 4.12: Gold Fields return distribution

The results of the VaR and ES models are presented in Table 4.9. The losses derived by the ES model range between R4,33 to R9,52 while the losses according to VaR ranges between R2,73 to R6,68. At a 99% confidence level, the historical simulation model gives the highest possible loss of R6,68 while the variance-covariance method gives a loss of R5,67 and R5,28 from the Monte Carlo Simulation. At a 95% confidence level, historical simulation method gives lower losses compared to the other two VaR models.

Table 4.9: Gold Fields Value at Risk and Expected Shortfall results

	Variance: Covariance Value at Risk			Historical Simulation Value at Risk			Monte Carlo Simulation			Expected Shortfall	
	Mean	0,00077		Number of observations :1042			Number of observations :1042				
	STD	0,03008									
Confidence Level	**VaR**		**Cents**	**HVaR**		**Cents**	**VaR**		**Cents**	**ES**	**Cents**
90%	10%	-0,041	-310,28	104,2	-0,035	-273,32	104,2	-0,041	-314,73	-0,0568	-433,57
95%	5%	-0,0524	-399,62	52,1	-0,050	-383,57	52,1	-0,056	-424,54	-0,0726	-553,32
99%	1%	-0,0744	-567,20	10,42	-0,087	-668,52	10,42	-0,071	-540,46	-0,1249	-952,53

The outcomes of the Kupiec test rejects the results of all the VaR models at the 90% and 95% confidence level. At the 90% and 95% confidence levels, the likelihood ratio of the different VaR models ranges between 4,368 and 9,127. The Basel traffic light on the other hand accepts all the models as the failure falls within the expected exception zone. The Basel Committee classifies this as two possible type errors where the model accepts incorrect simulations or rejects incorrect outputs. These are called type 1 and type 2 errors. The only output that are accepted from the risk modelling of Gold Fields are the 99% confidence level test.

The Traffic light test for Monte Carlo Simulations at a 90% confidence level indicates the inaccuracy of the VaR models as seen in Table 4.10. These outcomes could be produced by both accurate and inaccurate models with relatively high probability, even though they are more likely for inaccurate models. Backtesting results in the yellow zone generally cause an increase in the multiplication factor, depending on the number of exceptions. The outcomes of the ES model in the analysis of Gold Fields proves to be effective based on backtesting results and the possible loss exposure as compared to VaR methods.

Table 4.10: Gold Fields backtesting outputs

Variance: Covariance Value at Risk									
Confidence Level	**VaR**		**N**	**Expected Exceptions**	**Realised Exceptions**	**POF-test LR**	**Critical Value 95%**	**Kupiec Test Result**	**Basel Traffic Light**
90%	10%	-0,0407	250	25	12	9,127	3,84	Reject	Green
95%	5%	-0,0524	250	13	4	8,185	3,84	Reject	Green
99%	1%	-0,0744	250	3	2	0,108	3,84	Accept	Green
Historical Simulation Value at Risk									
90%	10%	-0,0359	250	25	15	5,113	3,84	Reject	Green
95%	5%	-0,0503	250	13	6	4,368	3,84	Reject	Green
99%	1%	-0,0877	250	3	2	0,108	3,84	Accept	Green
Monte Carlo Simulation									
90%	10%	-0,0391	250	25	14	6,294	3,84	Reject	Yellow
95%	5%	-0,0506	250	13	5	6,071	3,84	Reject	Green
99%	1%	-0,0785	250	3	2	0,108	3,84	Accept	Green
Expected Shortfall									
Confidence Level	**VaR**		**N**	**Expected Exceptions**	**Realised Exceptions**	**POF-test LR**	**Critical Value 95%**	**Kupiec Test Result**	**Basel Traffic Light**
99%	1%	-0,1249	0	3	1	N/A	3,84	N/A	Green

4.5.3. Harmony Gold

Harmony Gold had several difficult years from 2012 to 2015, with the share price falling from R114 to R8.70 by the end of 2015. The company suffered losses of a R4.5 billion loss in 2015 (Harmony Gold, 2015). This was mainly due to falling gold price, higher operating costs and a challenging economic environment. The high volatility forced the company to undergo extensive restructuring of the company's asset portfolio, with a focus on cutting costs, improving labour productivity, increasing overall mining grade and ensuring that only safe and profitable ounces are mined. The restructuring included a life of mine optimisation process and placing operations such as Target on care and maintenance. Figure 4.13 indicates the share price performance for Harmony gold highlighting the rises and declines of the share price.

Figure 4.13: Harmony Gold adjusted closing price: June 2015-June 2019

Source: Sharenet (2019)

Volatility on Harmony's returns can be observed mainly in 2015 as seen in Figure 4.14, this can be attributed to the revision of the company's business strategy for financial year 2016. The review resulted in an impairment of R 2,1 billion for Hidden Valley and an additional R1 billion from Doornkop mine (Harmony Gold, 2015).

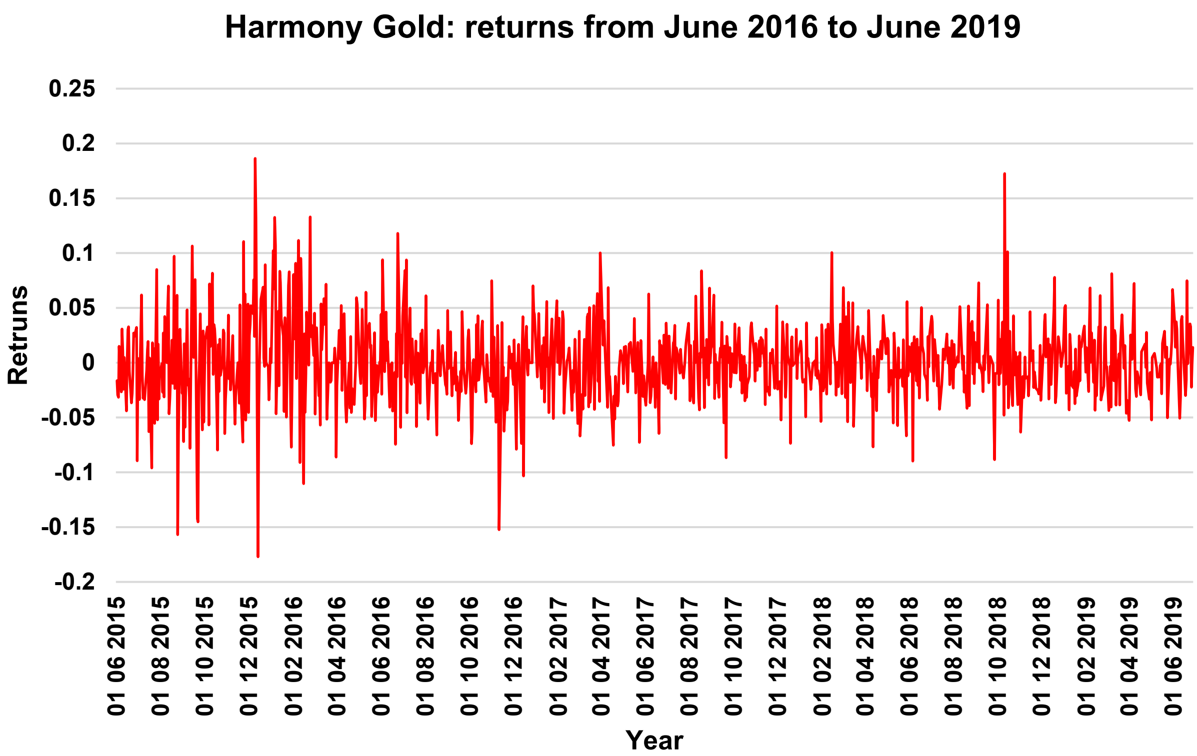


Figure 4.14: Distribution of returns for Harmony Gold: June 2015-June 2019

Table 4.11 and 4.12 indicate the outcomes of the VaR, ES risk measure and backtesting outcomes of the company. At higher confidence levels of 99%, the VaR risk models give possible losses that range between R2,64 to R2,84 while at lower confidence levels the model predicts losses between R1,30 to R1,94. The Historical Simulation model predicted higher losses compared to the variance-covariance and Monte Carlo Simulations at the 99% confidence level whereas the opposite occurred at lower confidence levels. The possible losses for Harmony Gold range between R2,00 at a lower confidence level of 90% to R4,14 at a higher confidence level of 99% when applying the ES method.

Table 4.11: Harmony Gold Value at Risk and Expected Shortfall results

	Variance: Covariance Value at Risk			Historical Simulation Value at Risk			Monte Carlo Simulation			Expected Shortfall	
	Mean	0,00059		Number of observations :1042			Number of observations :1042				
	STD	0,03742									
Confidence Level	**VaR**		**Cents**	**HVaR**		**Cents**	**VaR**		**Cents**	**ES**	**Cents**
90%	10%	-0,0474	-150,34	104,2	-0,0411	-130,53	104,2	-0,0429	-136,15	-0,063	-200,69
95%	5%	-0,061	-193,48	52,1	-0,0543	-172,20	52,1	-0,0582	-184,82	-0,079	-251,29
99%	1%	-0,0865	-274,42	10,42	-0,0898	-284,98	10,42	-0,0839	-266,44	-0,1306	-414,37

The likelihood test rejected the results of the variance-covariance model at the 90% and 95% confidence level. When the same models are tested against the traffic light test, the results are passed as the realised exceptions fall within the acceptable limits.

Table 4.12: Harmony Gold backtesting output

Variance-Covariance Value at Risk									
Confidence Level	**VaR**		**N**	**Expected Exceptions**	**Realised Exceptions**	**POF-test LR**	**Critical Value 95%**	**Kupiec Test Result**	**Basel Traffic Light**
90%	10%	-0,0474	250	25	12	9,127	3,84	Reject	Green
95%	5%	-0,061	250	13	5	6,071	3,84	Reject	Green
99%	1%	-0,0865	250	3	2	0,108	3,84	Accept	Green
Historical Simulation Value at Risk									
90%	10%	-0,0411	250	25	17	3,168	3,84	Accept	Green
95%	5%	-0,0543	250	13	8	1,944	3,84	Accept	Green
99%	1%	-0,0898	250	3	0	N/A	3,84	Accept	Green
Monte Carlo Simulation									
90%	10%	-0,0472	250	25	31	0.415	3,84	Accept	Green
95%	5%	-0,0624	250	13	22	0,197	3,84	Accept	Green
99%	1%	-0,0911	250	3	1	0,108	3,84	Accept	Green
Expected Shortfall									
Confidence Level	**ES**		**N**	**Expected Exceptions**	**Realised Exceptions**	**POF-test LR**	**Critical Value 95%**	**Kupiec Test Result**	**Basel Traffic Light**
99%	1%	-0,1306	250	3	0	N/A	3,84	N/A	Green

4.6 Discussion of results

The accuracy of the VaR models was tested using the Kupiec's test with the results presented in the Appendices 7.1 to 7.6. The tests measured the Likelihood-Ratio (LR) test statistic using the number of realised exceptions. Equation 9 was used to determine the test statistics which is compared to the critical value of 3,84. The accuracy of the model is critical as VaR is defined as the maximum loss and it implies that the loss will not exceed the given value at specified confidence level.

The Kupiec test results were presented under each company's results. It is noted that the different VaR models at the various confidence levels yield different outcomes from the LR test. Companies such as Sasol that experienced significant shock in their share prices failed most of the test while those who experienced stable growth over the period like Exxaro have pass the Kupiec test. The impact of shock to a company's share price and the outcomes of backtesting are supported by Goorbergh & Vlaar (1999). Goorbergh & Vlaar (1999) concluded that some models fail due to the market risk in the preceding periods being smaller than those under review. Although VaR requires a minimum of trading 250 days, the share performance of the previous trading days will have an impact on the overall effectiveness of the risk measure.

The results indicate that all historical simulation method passes the LR test at various confidence levels except for Gold Fields and Anglo Gold Ashanti. Khadar (2011) found that historical simulation models predict accurate VaR measures at short trading day periods however, the model produces more failure rates as the trading day sample size increases. The test condition for these models was conducted under a window size of 250 samples, the failure rates are likely to increase as the window sizes go wider. The failure of some historical simulation methods in this study is supported by other studies by Khadar (2011) and Cabedo & Moya (2003) who found that historical simulation methods are less accurate with risky assets such as oil and gold.

The outcomes of the research study indicate that some of the variance-covariance methods fail the test, this indicates a principal floor in the assumption of normality underlying assets. Volatility, skewness and kurtosis are critical factors that affect the distribution of the data. Sections 4.2 and 4.3 provide details on the distribution properties of the data, most of the statistical distributions are either leptokurtic or platykurtic as opposed to mesokurtic which is the basic assumption of the variance-covariance method. The shorter trading day window periods have higher volatility than longer periods because the variance-covariance method measures a moving- average of volatility which is dependant of the sample size (Jorion, 2007). This explains why some of the variance-covariance models failed the backtesting results in the 250-trading day period.

The Basel traffic lights is the simplest form of backtesting VaR methods applied in this analysis. Based on the number of violations, the models were classified into three colours: Green representing accurate loss estimations as the models have a low probability of accepting inaccurate results, yellow representing a combination of accurate and inaccurate losses depending on the ability to demonstrate the fundamental soundness of the VaR model and red representing automatic rejection of VaR model. This backtesting approach was mainly used for regulatory purposes at the 95% confidence level and exception ranges are given by the Basel regulatory framework. For this research study, Table 4.13 was used to analyse the cut-off regions for the number of exceptions using the traffic light approach for the three VaR confidence levels. Models with better accuracy levels were classified under the green code while models with lower levels accuracy were classified in the red zone.

Table 4.13: Traffic light test – Basel Committee

Confidence Level	**Zone**		
	Green Zone	**Yellow**	**Red Zone**
99%	0 - 4	5 - 9	10+
95%	0 - 17	18 - 26	27+
90%	0 - 32	33 - 43	44+

The findings of the research indicate that most of the VaR outcomes at various confidence levels on coal companies range from green to yellow zones while gold companies are all in the green zone with exception to Gold Fields. The outcomes of the backtesting results in relation the likelihood test ratio results indicate that the accuracy of the VaR methods are inadequate to measure the worst-case scenario for the various mining companies.

A traffic light approach as proposed by Costanzio & Curran (2018) was applied to the backtesting of ES and it was found that all the models at a 95% confidence level fall within the recommended range. This indicates that the ES models can be applied to any gold and coal company with a high-level certainty on the possible worst-case losses generated by the models. The higher values predicted by the ES models enables investors to have a better indicate of possible losses in the various companies.

4.7 Chapter summary

The performance of the different VaR and ES methods varied across each company, commodity and confidence level. It was found that the relationship between Monte Carlo Simulation, variance-covariance and historical simulation varies at different confidence levels and companies. The possible loss estimates from the historical simulation methods were higher than the variance-covariance in some companies while the opposite applied in others. The losses estimate by the ES models was also higher the VaR in all the companies analysed.

This chapter presented the results and analysis of the backtesting outcomes for each of the companies under review. The Kupiec test was applied to the VaR methods to measure the number of violations. A model satisfying the criterion of coverage is expected to have the same proportion of VaR violations as the level of significance of the estimate, as these are assumed to follow a binomial distribution. It was found that some of the VaR models failed the Kupiec test as the violations were above the exceptions. The next chapter will conclude the findings of the research and provide recommendations.

5. CONCLUSION AND RECOMMENDATION

5.1 Introduction

This chapter provides findings of the study in relation to the research objectives and problem statement. Section 5.2 presents a summary of the findings in relation to the research objectives. The recommendations and suggestions that could be considered for future work are presented in Sections 5.3 and 5.4 respectively.

5.2 Conclusions

The aim of this study was to identify the most appropriate method of measuring market risk in mineral commodities given the volatility experienced by the South Africa mining sector. The focus was on blue collar gold and coal companies as these play a significant role in the overall economy and are highly exposed to volatility. There are various methods such as Standard Portfolio Analysis used to measure risk exposure however, VaR and ES models were identified as the common methods for measuring market risk exposure.

The research predicted VaR and ES methods using Microsoft Excel for 1-day horizons with input data of just over 1042 observations. The use of a longer observation period provided valuable insight into the relative performance of the methods over various market volatilities. The accuracy level of these VaR methods were backtested to verify the accuracy of each model.

Comparing the results of the VaR methods found that models such as the variance-covariance are not effective as the assumption of normality fails. One of the flaws of these methods is due to data distribution rarely following normal distributions. In the case of volatile portfolios such as gold, the method fails to capture the optimal risk. ES methods were able to provide the worst possible losses and the exceptions derived from the backtesting complied with the Traffic light test requirements for possible exceptions.

From the analysis, historical simulation methods predicted the highest ranges as compared to Monte Carlo Simulation and the variance-covariance methods. When comparing historical simulation approaches and ES to determine overall risk, ES models resulted in a higher estimate for daily losses for the portfolios, although the portfolio's return distribution were leptokurtic or platykurtic.

The historical simulation loses derived from Exxaro ranged between R5,73 to R13,12 while ES models predicted possible losses ranging between R9,01 to R17,28.In the case of Sasol, the historical simulation loses ranged between R7,84 to R19,93 while ES models predicted higher losses within the ranges of R12,85 to R26,93. This difference in estimates for daily losses was due to the fact that ES is the average of the daily losses that may occur in the tails whereas VaR is simply the p^{th} percentile for a return distribution. VaR does not factor in the magnitudes of losses above the p^{th} percentile while ES does.

The gold companies have trends like the coal companies where Historical simulations were yielding the highest possible losses amongst VaR methods however, these were lower than the results derived from the ES models measures. Anglo Gold Ashanti had the highest possible losses in comparison to Harmony Gold and Gold Fields with a risk exposure range of R8,90 to R24,52 in comparison to R1,35 to R4,14 and 2,73 to 9,52 respectively. The maximum possible risk exposure is directly related to the overall company share prices. Companies with high share prices like Anglo Gold Ashanti have a higher risk exposure as compared to companies with relatively lower share prices like Gold Fields.

The research finds that ES models are a better measurement of risk as VaR fails to accurately measure risk in worst case scenarios. This is in line with the literature review present in support of the study. Keuster *et al.* (2006) found that the most used VaR methods, namely the delta normal, Monte Carlo simulation and historical simulation, severely underestimate market risk as found in this research study.

5.3 Recommendations

The application of ES method is recommended as a risk measure when analysing market exposure in mining companies with significant exposure such as gold and coal. Based on the results of the study, VaR methods are found to have various limitation for companies that do not have returns with normal distribution properties. A key consideration is the choice of confidence level that would be applied in the analysis, a 95% confidence level is recommended as most of the risk measuring models are comparable at this confidence level including the outcomes of the backtesting process. The outcomes of the models at a 95% confidence level is in line with Risk Metrics assumption of 95% confidence as a baseline.

5.4 Recommended future studies

This research focused on coal and gold mineral commodities as these are part of the risky mineral commodities with a significant role in South Africa. Based on the findings of this research, a similar study can be conducted using different commodities as most of the available research on VaR and ES models is mainly focused on oil. Additional studies on risk measurement in other mineral commodities would improve the available knowledge on risk exposure and management in various commodities other than oil. The back testing of VaR methods was restricted to 250 observation, future work could consider the backtesting of models beyond the regulated time period with the aim of understanding the impact on the overall performance of risk measurement models.

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7. Appendices

The Appendices 7.1 to 7.5 for this research study are submitted as a Microsoft Excel attachment labelled as follows:

The data can be accessed through the link below:
https://drive.google.com/file/d/1aGfWYmfdRTUre98Klniw_j1KFe-P-k1X/view?usp=sharing

7.1. Input Share price data for Exxaro Limited from (period)

7.2. Input data for Sasol

7.3. Input data for Anglo Gold Ashanti Limited

7.4. Input data for Gold Fields Limited

7.5. Input data for Harmony Gold

7.6. Descriptive statistics for coal mining companies

Coal Companies													
	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count
Exxaro	0,09%	0,09%	0,09%	0,00%	2,93%	0,0009	3,0430	0,1064	29,82%	-12,61%	17,21%	95,47%	1042
Sasol	-0,01%	0,06%	0,00%	0,00%	1,99%	0,0004	4,2503	-0,4284	22,07%	-13,92%	8,16%	-6,49%	1042

7.7. Descriptive statistics for gold mining companies

Gold Companies													
	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count
Anglo Gold Ashanti	0,08%	0,09%	0,00%	0,00%	3,01%	0,0009	1,6905	0,2888	23,33%	-11,20%	12,12%	79,94%	1042
Gold Fields Limited	0,06%	0,10%	0,00%	0,00%	3,23%	0,0010	3,4861	0,0299	31,70%	-16,03%	15,67%	66,56%	1042
Harmony Gold	0,06%	0,12%	0,00%	0,00%	3,74%	0,0014	2,4775	0,1873	36,34%	-17,71%	18,63%	61,41%	1042

7.8. Percentage Points of the Chi-Square Distribution

Degrees of Freedom	Probability of a larger value of x^2								
	0.99	0.95	0.90	0.75	0.50	0.25	0.10	0.05	0.01
1	0.000	0.004	0.016	0.102	0.455	1.32	2.71	3.84	6.63
2	0.020	0.103	0.211	0.575	1.386	2.77	4.61	5.99	9.21
3	0.115	0.352	0.584	1.212	2.366	4.11	6.25	7.81	11.34
4	0.297	0.711	1.064	1.923	3.357	5.39	7.78	9.49	13.28
5	0.554	1.145	1.610	2.675	4.351	6.63	9.24	11.07	15.09
6	0.872	1.635	2.204	3.455	5.348	7.84	10.64	12.59	16.81
7	1.239	2.167	2.833	4.255	6.346	9.04	12.02	14.07	18.48
8	1.647	2.733	3.490	5.071	7.344	10.22	13.36	15.51	20.09
9	2.088	3.325	4.168	5.899	8.343	11.39	14.68	16.92	21.67
10	2.558	3.940	4.865	6.737	9.342	12.55	15.99	18.31	23.21
11	3.053	4.575	5.578	7.584	10.341	13.70	17.28	19.68	24.72
12	3.571	5.226	6.304	8.438	11.340	14.85	18.55	21.03	26.22
13	4.107	5.892	7.042	9.299	12.340	15.98	19.81	22.36	27.69
14	4.660	6.571	7.790	10.165	13.339	17.12	21.06	23.68	29.14
15	5.229	7.261	8.547	11.037	14.339	18.25	22.31	25.00	30.58
16	5.812	7.962	9.312	11.912	15.338	19.37	23.54	26.30	32.00
17	6.408	8.672	10.085	12.792	16.338	20.49	24.77	27.59	33.41
18	7.015	9.390	10.865	13.675	17.338	21.60	25.99	28.87	34.80
19	7.633	10.117	11.651	14.562	18.338	22.72	27.20	30.14	36.19
20	8.260	10.851	12.443	15.452	19.337	23.83	28.41	31.41	37.57
22	9.542	12.338	14.041	17.240	21.337	26.04	30.81	33.92	40.29
24	10.856	13.848	15.659	19.037	23.337	28.24	33.20	36.42	42.98
26	12.198	15.379	17.292	20.843	25.336	30.43	35.56	38.89	45.64
28	13.565	16.928	18.939	22.657	27.336	32.62	37.92	41.34	48.28
30	14.953	18.493	20.599	24.478	29.336	34.80	40.26	43.77	50.89
40	22.164	26.509	29.051	33.660	39.335	45.62	51.80	55.76	63.69
50	27.707	34.764	37.689	42.942	49.335	56.33	63.17	67.50	76.15
60	37.485	43.188	46.459	52.294	59.335	66.98	74.40	79.08	88.38

Source: Passel, (2016).