**BINDURA UNIVERSITY OF SCIENCE EDUCATION**

 **FACAULTY OF COMMERCE**

 **DEPARTMENT OF ACCOUNTANCY**

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**MODELLING MARKET RISK USING BOOTSTRAPPING AND FILTERED HISTORICAL SIMULATION. A CASE STUDY OF OLD MUTUAL.**

 **BY**

 **RUFARO T MACHINYA**

 **B190582B**

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# DEDICATION

I dedicate this dissertation to my Dad and Mom who supported me in my career and they made this journey easier.

# ABSTRACT

For any organization, managing financial risk must include market risk. Companies utilize a variety of quantitative strategies, including Expected Shortfall (ES) and Value at Risk (VaR), to manage market risk. VaR, a commonly used indicator of market risk, assesses the largest loss an organization may reasonably expect to suffer over a particular time period with a certain level of confidence. VaR has some drawbacks, such as the inability to account for the tail risk, which is the likelihood of extremely large losses beyond a certain point. Companies use ES, which calculates the average loss that is anticipated to occur over a specific threshold level, to get around this restriction. The historical data, which is used to calculate the probability distribution of market returns, is one of the main inputs in VaR and ES models. However, historical data might not always be trustworthy, particularly in times of economic crisis or market volatility. In these circumstances, organizations estimate the probability distribution of market returns using different techniques like bootstrapping and filtered historical simulation (FHS). This study examines the modeling of market risk using daily equity returns from OLD MUTUAL portfolio over time to assess the forecasting performance of Value at Risk (VaR). The paper employs VaR models like bootstrapping and filtered historical simulation. As part of this procedure, the residuals from the filtered historical simulation GJR-GARCH will be bootstrapped, and a comparison between the residuals that have been adjusted for volatility and those that have not will be made. The findings indicate that a portfolio that has been volatility-adjusted will be more successful. In conclusion, utilizing bootstrapping and FHS to simulate market risk is an efficient way for businesses to manage their market risk. A more accurate estimate of the probability distribution of market returns is provided by the model, which can also assist businesses in making more informed judgments regarding their risk management plans.

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#  CHAPTER l

## 1.0 Introduction

There is a wealth of information available on backtesting techniques and VaR or Expected Shortfall (ES) calculation for market risk modeling. But the set of guidelines released by the Basel Committee in January 2016 under the heading "Minimum capital requirements for market risk," also referred to as the Fundamental Review of the Trading Book, forces a reevaluation of current methods.

 Additionally, regulators have voiced worries about excessive variability of assets with a risk weight connected to market risk. Risk model results do depend on the modeling decisions made. In light of the new regulatory framework, this paper aims to reveal the effects of subjective decisions made in relation to risk models, capital market requirements, back testing, and risk comparability. My study concentrates on the decay factors in filtered news and how quickly the risk measure adjusts to the arrival of news. In other words, the decay factors used in weighted historical simulation techniques. These parameters are established at the banks' discretion, resulting in a trade-off between the capital metrics' conservatism and the resilience of risk models during turbulence. Basel 3's new structure is designed to make extant regulatory requirements more stringent by switching from a hybrid of current VaR and stressed VaR to a fully stressed Expected Shortfall.

When things are going well, investors normally forget to take the risks that are part of their portfolios into consideration. Prior to the financial crisis of 2008, this had become a significant problem, and the crisis served as a reminder to many companies of the value of risk assessment. Due to the significance of banks in our economy, this was particularly evident for investment banks, which suffered significant losses as a result of some risky assets in their portfolios that they had not properly accounted for. Regulations in place mandate that banks stress test their portfolios to assess risk exposures. In the light of such occurrence of high trading activity and instances of financial crisis as mentioned earlier there have been new studies emphasizing the need for market players such as banks, hedge fund managers and traders to develop reliable market risk measurement techniques. Market risk is characterized as the potential loss brought on by falling financial market prices. It consists of stochastic market elements like interest rates, foreign exchange risk, commodity and equity risk, as well as other risks.

## 1.2 Background of the study

When things are going well, investors frequently forget to take the risks that are part of their portfolios into account. Prior to the financial crisis of 2008, this had become a significant problem, and the crisis served as a reminder to many organizations of the value of risk assessment. Due to the significance of banks in our economy, regulations are in place that require banks to stress test their portfolios in order to assess risk exposures. This is done in order to prevent losses caused by some risky assets in their portfolios that they did not properly account for. There have been recent studies highlighting the need for market participants like banks, given the high trading activity and instances of financial crisis previously mentioned.

Traders and hedge fund managers create trustworthy methods for measuring market risk. The possible loss brought on by falling prices on the financial market is known as market risk. It consists of stochastic market elements like interest rates, foreign currency risk, commodity and equity risk, as well as other risks. It is also known as systematic risk, referring to the uncertainty associated with any investment decision. Value at risk models are one method that has been developed in the books. These algorithms calculate the market risk of a financial asset portfolio.

These models have a lot to offer because they sum up the market risk for the complete portfolio. Additionally, the value at risk measures directly the loss of portfolio value, which is a major factor in the initial risk assessment. The financial and\regulatory communities recognize this model, that recognition is evident for their expanding or growing use. As an example, the use of such models was approved by the Basel Committee on Banking Supervision, subject to crucial qualitative and numeric standards.

The length of time over which market risk should be measured and the confidence level at which market risk is measured are the two most crucial components of value at risk models, and risk management has chosen these components accordingly. Value at risk offers a standard, reliable way to assess risk for various positions and risk factors. As a result, it can be used with any kind of portfolio and allows us to contrast the risks of various portfolios. It measures the risk connected to a fixed income position in a manner similar to how it measures the risk connected to a stock position.

## 1.3 Problem statement

Choosing and administering a basket of stock indexes is fraught with uncertainty. Any transaction in the stock market is subject to market risk because prices could increase or decrease in the future. The requirement for some level of certainty when assembling a basket of equities to be able to minimize losses going forward leads to the need to quantify market risk.

## 1.4 Research Objectives

¡. Using bootstrapping and filtered historical modelling to measure market risk.

¡¡. To assess how market risk and volatility risk can be measured and managed using daily equity opening, closing values, as well as to numerically illustrate the measures.

¡¡¡. To calculate and understand value at risk under parametric circumstances.

## 1.5 Research questions.

1. How does bootstrapping and historical modelling accurately predict market risk over time?

2. How can market risk be measured and managed using daily equity as well as to numerically illustrate the measure?

3. What is the extent to which value at risk can be used to measure financial risk under parametric circumstances?

## 1.6 Hypothesis statement

H0: Price and volatility influence how the market risk varies.

H1: Price and unpredictability have no impact on how the economic exposure varies.

## 1.7 Significance of the study

 **To the researcher**

In fulfillment of the prerequisites for the Bachelors of Accountancy honors degree of Bindura university science education faculty of commerce. The fact that it would improve critical thinking skills makes this study essential to the experts. By examining information and comprehending findings, study mastery can turn hypothetical proof into clinical usage and give the researcher a practical knowledge of what it takes to pursue out another thesis.

 **To the Bindura University.**

The study offers material that other pupils as well as scholars on the subject can examine in the years ahead.

**To the Regulators**

The study will support the development and application of market risk-aware policies by policymakers in the financial sector.

**To the Investors.**

This study will help financiers in the financial industry to recognize the main macroeconomic influences on the development of the financial sector in Zimbabwe, including regulation.

## 1.8 Assumptions

a) Reliable and accurate information is to be acquired.

b) The economic factors change over time and are not constant.

## 1.9 Delimitations of the study

By examining the crucial macroeconomic variables that affect performance of the financial sector in Zimbabwe, this study aims to close the knowledge deficit by concentrating on a specific underdeveloped nation. As a result, the goal of this study is to generate interest in future research in this field that is based on less developed markets and to provide a fertile ground for that research. The result of this study will also serve as a foundation for discussion of empirical research in developed markets and inspire Zimbabwean academics to investigate this field of study in order to improve the current hypothesis.

The GJR GARCH historical simulation with filtering and bootstrapping of the residuals was used in the research to focus on value at risk. For the two conditions which are volatility adjusted and non- volatility adjusted- daily equity returns from the Zimbabwe stock exchange were used as data source.

Daily equity returns from the Zimbabwe stock exchange where used ranging from 2020 to 2023 for information extracted or that belongs to OLD MUTUAL (CABS BANK).

## 1.10 Limitations

The instability of the country and its currency is our main obstacle. It is extremely challenging to develop a model based on stock prices while these are experiencing the high rates of inflation that impact our economy each year. Prices are erratic.

## 1.11 Definition of terms

Abbreviation

EMA ……. Exponentially moving average

ZSE……… Zimbabwe stock exchange

VAR ………. Value at risk

ES……… Expected Shortfall

FHS…. Filtered historical simulation

I.I.D… Independent and Identically Distributed

Value at Risk (VAR) - Is a metric for loss risk associated with assets. It calculates the amount that, under typical market conditions, a set of investments could potentially lose over the course of a specified time frame like a day.

Market risk- The council of Europe Development bank (November 2022) defines market risk as “the risk of a loss resulting from adverse changes in interest or currency exchange rates.”

Expected shortfall- by definition, ES takes into account the loss above the VAR threshold. Given that the loss exceeds the VAR threshold, is the conditional expectation of loss. By averaging all values in the distribution that are worse than the portfolio’s VAR at a specific confidence level, ES is determined,

Filtered historical simulation- According to Giovanni Barone (2021), it is a method for generating scenarios for the prices of speculative commodities the probability distribution of potential asset (risk factor) values is constructed by FHS using a mix of nonlinear econometric models and historical returns.

## 1.12 Chapter Summary.

Measuring market risk is our main concern and the center of focus. The research used the filtered historical simulation GJR GARCH and the residuals were then bootstrapped with a focus on value at risk. Two criteria were given: volatility adjusted and non-volatility adjusted, and daily equity returns from the Zimbabwe Stock Exchange were used as the data from January 2020 to January 2023, daily equity results from the ZSE were used. The study is much concerned on accounting for risks that may be associated with investments in banks. On chapter two we will be focusing on reviewing all the relevant body of literature that has drove me to undertake such an investigation.

# CHAPTER ll

 **LITERATURE REVIEW**

## 2.1 Introduction

In this chapter, the researcher concentrated on reviewing the entire corpus of pertinent material that inspired me to conduct this inquiry. This chapter includes both theoretical and empirical research on the subject of the study that was done by different researchers, noting their varying findings. Value at risk, which will be addressed in relation to its inception and growth, was sparked by the desire to provide answers to concerns like what an investor would lose on an investment under typical market conditions. A thorough introduction to historical simulation will also be included in this chapter.

## 2.2 Theoretical Literature Review

### 2.2.1 Market Risk

The practice of risk management enables management of the organization to appropriately trade off risk and reward. Management must put in place a procedure by which the business may achieve this goal efficiently. Market risk is the chance that the financial market's volatile or falling prices will cause a loss. It also contains stochastic market risk elements like interest rates and commodity prices. Historically, the inherent to the entire market risk of a portfolio has been the sole focus of market risk management for portfolios. Having a sizable and diversified portfolio won't make this risk disappear completely (Bowen, David and Hutchinson, 2016).

The application of a factor model, according to C. Alexander (2014), connects the distribution return of a portfolio to the distributions return of its risk component returns. The systematic risk is often referred to as unidentified risk. A multi-factor model, with risk factors that are more than one, is often predicted making use of a multiple linear regression, while the independent variables are the returns on numerous risk factors and the dependent variable is the return on a single asset. R.Cont. (2001) et al. The risk of factor returns, the systematic risk, and the net portfolio sensitivity to each risk component are then determined.

According to Davis (2021), the risk in a portfolio that is unrelated to the returns from risk factors is the specific risk, also known as the residual risk. It is the risk that results from a linear regression model of asset return on risk factor returns' variance of the residuals. The specific risk associated with that asset may be high if the model used to explain the returns of that asset in a portfolio only has a few components. The specific risk can, however, be reduced to almost zero with a sufficiently large and diverse portfolio because it is dispersed among a large number of assets in many economic sectors.

Market Risk became more successful in measuring company risk with the adoption of (VaR), before var there was:

Gap analysis: The methodology is called gap analysis, was first developed by financial organizations to come with an approximate estimation of the exposure to interest rate risk.

D. Dissanayake (2021) points out the picking of an appropriate period time (for instance, one year out) is the first step in the gap analysis process. The amount of our liability or asset portfolio that is set to undergo a price change during that time is determined, and the resulting values provide us the rate-sensitive assets and rate-sensitive liabilities for the chosen horizon according to F. Pirola (2019). A change in interest rates results in a change in our interest-rate exposure, which is expressed as a shift in net interest income. Gap analysis is straightforward, but it has limitations since it only considers interest rate risk that is present on the balance sheet, it looks at how interest rates affect income rather than asset or debt values, and the results could depend on the time period used.

Time Evaluation Duration analysis is a second established technique utilized by financial organizations to assess interest-rate risks (Lazarus, 2023). The weighted average term to maturity of a bond's cash flows, with the weights being the present value of each cash flow in relation to the present value can be used to determine the duration of a bond or other fixed-income instrument.

### 2.2.2 Origin and development of Value at Risk

According to Tylor and Francis (2022), value at risk, which is measured using confidence levels between 90% and 99%, such as 90%, 95%, or 99%, is the measurement of the worst projected loss over a certain period under the ordinary market conditions. The financial instrument's holding term might range from one day to one year. In a nutshell, value at risk is a measurement of the largest loss that may occur during a specific time period with a specified confidence range. Financial firms can calculate the amount of capital reserves they require to make up losses by using var.

Consider the following scenario for a deeper comprehension of value at risk in general: an analyst estimates that a portfolio's 1-day VaR is $1 million with a 95% confidence level. It suggests there is a 95% likelihood that the largest losses would not total more than $1 million in a single day. In other words, the probability that the portfolio losses on a given day would exceed $1 million is merely 5%.

Penikas, Skarednova and Surkov (2021) noted that, financial entities started creating internal methods to assess and add up total risks throughout the organization in the latter part of the 1970s and early 1980s. They started developing these models for their own risk management needs as businesses grew more complicated. It was getting more challenging but also more crucial for businesses to total their risks while taking into consideration how they interacted with one another, but they lacked the tools to do so. Additionally, these businesses were having trouble managing risks across a variety of employment.

They would impose restrictions on traders and asset managers, but because of the information and management systems available at the time, the restrictions were applied gradually, resulting in a number of contradictions and other unfavorable outcomes. Because they encountered arbitrary boundaries, risks were taken without sufficient consideration of their overall effects on the company, and reducing risk in one area rarely permitted more risk in other areas, good trades or investments would be neglected (J Patton, F Ziegel and R Chen, 2019). Effective capital allocation was also under danger in a similar way. The biggest problem, though, may have been the absence of coordinated risk management. There was little consistency between the constraints imposed, the money granted, and the risks being taken since the committees in charge of setting and controlling restrictions and capital distribution lacked the tools essential to perform significantly better.

As businesses struggled with these issues, a general understanding that a sense of the likelihood of losses across the board was required eventually emerged. As a result, the idea of value at risk emerged, allowing businesses to more accurately assess their total risks and allocate money and restrictions to different business lines in a way that makes sense. The Risk Metrics system, created by JP Morgan, is the most well-known of these programs.

VaR modeling, which employs statistics to gauge the possibility of loss in either an instrument or a portfolio over a certain time period, has shown to be highly helpful in increasing market risk modeling. VaR stands for the maximum possible loss over a specified time frame and confidence level. Assume, for instance, that the VaR is $2 million, the time horizon is one week, and there is a 95% confidence level that the loss won't be greater than $2 million. In other words, this means that there is only 5% chance that the losses will exceed $2 million dollars. The confidence levels are set from 95% to 99% as per requirements by the Basel set of rules for banks stressing their portfolios Barrera et al (2022).

### 2.2.3 Advantages of VaR implementation

Financial organizations appreciate it so much (this method is known as risk budgeting). Value at Risk offers a standard, reliable way to quantify risk that is applicable to all kinds of situations and risk variables (Taylor, 2019). Value at risk can be implemented to any type of investment and used to make a comparison of the risks under different portfolios. Similar to how risk associated with an equity position is measured, risk associated with a constant income investment is also measured. Value at risk is a definite advancement over other traditional methodologies like duration and convexity, which are only applicable to fixed income holdings, Greek risk measures, which are only applicable to derivatives positions, and portfolio theory approaches, which are applicable to equity and comparable (such as commodity) positions.

Ahmadi and Pichler, (2017), find that value at risk get us in a prominent position to account for the ways that various risk variables interact (or correlate) with one another while aggregating the hazards of positions and sub-positions into a broad measure of portfolio risk. Another benefit of VaR is that it allows for the aggregation of component hazards, which is not supported by the majority of traditional risk measurements (G. Dionne, 2013). In contrast to many previous techniques, which either only consider risk variables one at a time (such as Greek measurements) or alternatively turn into simplified versions to combine several risk components s into one, VaR is holistic in that it fully accounts for all driving risk factors.

VaR is also holistic in that it emphasizes evaluation of the entire portfolio, frequently at the firm-wide level, as opposed to merely specific holdings within it. VaR is probabilistic and provides a risk management with important details on the probability connected to certain loss amounts.

VAR is merely one metric that provides you with a broad picture of the level of risk in the portfolio. Value at risk is presented as portion of the portfolio’s worth or as a number of units of exchange (such as dollars or euros.) The ease with which value at risk may now be assessed and used in analysis is one of its key advantages.

Additionally, different asset classes and different portfolios may have their VAR measured and compared. Stocks, bonds, currencies, derivatives, and other price-sensitive assets are all subject to Value at Risk. It allows them to analyze the profitability and risk of various units and distribute risk using VAR, which is why banks and other institutions from various sectors prefer its application.

## 2.3 Value at Risk criticisms

According to Evans and Whipple (2013) many financial institutions use VaR, however it is not without problems. To begin with, only historical data is utilized to determine the value at risk. When the past may not be a good predictor of the future and risk may be overstated or understated, the Var metric may be helpful. The financial industry is still debating whether the correlations between different financial prices are sufficiently stable to be relied upon when evaluating risk. It's also up for debate how to effectively simulate how the market's price volatility behaves. To avoid making subjective judgements about the possibility of future financial market volatility, an organization must rely heavily on past.

The extent of possible losses should prices move in a more unfavorable direction than is permitted by the chosen confidence level is not shown by a value at risk number, which is another drawback. The dollar amount at risk, for example, does not explain what would occur to a bank in the event of a 1 in 10,000 chance incidents. To manage the risks associated with such huge price fluctuations, banks are developing and the bank supervisors are requiring the implementation of more irrational measures, such as stress testing, in addition to the statistically based value at risk strategy. The design of stress scenarios, such as the suspension of the European Exchange Rate Mechanism, and analysis of how bank portfolios might react to them are both steps in the stress testing process (Wagner, Bluhm and Overbeck, 2016).

Third, Chainika Thakar (2022) averred that, there are benefits and drawbacks to the relative simplicity with which a value at risk calculation may distil exposures across a wide range of products and markets into a single number. Value at risk's appeal has primarily been due to its ease of use, particularly when used to present data summaries to top management at a bank. The issue with this, though, is that a highly aggregated statistic like this might conceal risk exposure mismatches across markets, institutions, or traders.

The majority of risk practitioners welcomed Value at Risk with varied degrees of enthusiasm, but some cautioned that it had more serious issues and may have some negative effects when used. The application of mathematical and statistical framework from the field of physical sciences, where they are well suited to social systems where they are typically flawed, was questioned by Nassim Taleb (2015) and Richard Hope (1998). The fundamental problem was whether or not the statistical and other presumptions behind value at risk were valid.

Benito, Abad and Lopez (2014) pointed out that these applications frequently ignore crucial aspects of social systems, including the dynamic interdependence and non-stationarity of many market processes, models’ validity is sometimes challenged by factors including how intelligent agents interact with and learn from their environment, which makes value at risk estimations susceptible to substantial mistakes. An associated claim was that Value at Risk predictions or numbers were too ill-defined to be very useful, and empirical data to support this claim is unsettling since it implies that various Value at Risk models may provide wildly different Value at Risk prediction and results.

In addition, value at risk gives false sense of security, it may be quite deceptive to think about risk vulnerability in context of var. Value at Risk is sometimes denoted to as "the biggest I can let go," especially when the confidence level is set at 99% during calculation. Khindanova, Irina and Rachev, 2019 says that despite the fact that you are aware of the value at risk’s true meaning, you could unintentionally get a false sense of reassurance from the 99% certainty. Unfortunately, 99% is not 100% in actuality, and here is where VAR's limits and their gaps in knowledge may be catastrophic.

Value at risk is a measure that may be determined using a variety of distinct, alternative ways, and different value at risk methodologies can result in different outcomes. The historical value at risk method, the Monte Carlo Simulation value at risk approach, the conventional variance-covariance parametric VAR are some of these techniques. The latter two are more adaptable to return distributions, but they also have significant limitations. Given that the different techniques are effective in different situations, having a wide range of options is helpful, However, given that diverse approaches may produce divergent results using the same portfolio, the representativeness of value at risk may be questioned Willumsen, Pelle, et al. (2019).

However, if you are aware of its limitations and don’t misinterpret it, value at risk can be beneficial. Value at risk can be used in conjunction with other tools and should only be a minor portion of the risk management process, especially those that adder the 1% worst case scenario that value at risk essentially ignores. As long you avoid getting a false sense of security from value at risk, it could be tremendously helpful Khindanova and Rachev (2019).

## 2.4 Historical Simulation Introduction

Financial institutions have been looking for years for the most effective way to sum up the risk exposure of their trading portfolio in one figure. Folklore holds that Dennis Weatherstone at J. P. Morgan was the man who first started this search. He was seeking for a means to notify the board of the financial organization about meaningful risk exposure without requiring the board members to possess a lot of technical knowledge (S Navidi, Shokoofeh and Banihashemi, 2017). The idea of a hazard-revealing statistic has become so widely accepted that it is now the foundation for a number of risk management programs and recommended legal methods for capital control. Despite the fact that this risk measuring concept is widely accepted, there is still no consensus on how to properly implement this risk assessment concept.

According to Forster, Piers M, et al (2013), in order to create a thorough risk measurement statistic, a projected distribution of the trading portfolio's returns at the conclusion of a specified holding time is used as the source of information. Finance professionals have concentrated their attention on a statistic identified as Value-at-Risk, which is the level of returns at which there is a certain risk of having a return that is lower than that level. VaR is, in other words, a point that roughly represents a particular percentile of the distribution of portfolio returns. This point estimate is the only statistic from the anticipated return distribution used in VaR analysis in all instances that we are aware of. The contribution of this article is to develop a VaR estimator from an estimated portfolio return distribution, which is merely assumed to be constant and distinct, using kernel quantile estimation (Sheather and Marron, 2014). With the use of additional information on the distribution of the desired percentile, including a gauge of the estimator's accuracy, this method creates a nonparametric estimate of a continuous distribution of investment returns.

It is not until all of the components of the kernel quantile estimate are as follows that a full analysis of the findings of Liu, Song and Zhang (2022) with similarities to the current study is made.

Chapter 2: Discusses the advantages of assessing the precision of predicted VaR and historical simulation.

Chapter 3: Explains the suggested estimator and two alternatives that are used in three data points' worth of demonstrative computations.

Chapter 4: Calculates VaRs for a financial institution's real trading portfolios

Gurrola, Pedro and Murphy, 2015 emphasized that the Historical Simulation, a VaR estimation technique, is a different approach to put one of the more well-liked risk measuring methodologies into practice. Historical Simulation consists of three parts, which are as follows:

1: Exhibits how, in relation to the core risk factors, the earnings on every investment in the portfolio change. This representation typically takes the shape of a precise sensitivity to each component when applied to historical simulation. The positions are represented using either a linear or nonlinear approximation of the sensitivity to each risk component depending on a number of factors, including the trade-offs the financial institution chooses between calculation speed and accuracy.

2: A model that simulates the difference inside the underlying risk components. It's asserted that the historical simulation technique compares prospective shifts in the risk variables to previous changes in the risk factors... The empirical distribution of factor returns is another name for this. Because there are fewer relevant risk factors than there are instruments in the portfolio, modeling the risk variables causing fluctuations in portfolio value saves time for computation.

3: By connecting shifts in the risk factors to the positional factor sensitivities, the VaR can be calculated. The historical simulation method does this by calculating the changes in the positions' numbers that correspond to each historically recorded change in the risk variables. To determine the change that corresponds to the required percentile, rank the ensuing changes in portfolio value from smallest to largest. For instance, if 5000 days of prior risk factor changes are taken into account, the fifth percentile is represented by the portfolio's fifty-first lowest change.

The underlying premise of historical simulation is that the historically observed factor changes employed in the simulation are drawn from independent, identical distributions that are also relevant to the forecast. This is a feature of all VaR estimating methods. The variance-covariance method to VaR estimation's Risk metrics variant, which employs a parametric process GARCH by Francq and Zakoian, 2022 stands out as an important exception. The fundamental positive aspect of the histogram simulation technique is that it is not parametric, meaning that there are no explicit assumptions about the data's distribution are established, and no estimation of distributional parameters is required. The form of the return distribution is therefore determined by the data.

Due to this, Mourtzis (2020) discovered that the historical simulation technique gave accurate estimates of the first percentile of the distribution when the return distribution deviated from normality. The study used simulated spot foreign exchange portfolios. S. Navidi (2017) also came to a similar conclusion when researching stock and spot currency simulation portfolios.

If the historical sample period is too brief, the fundamental strategy of historical simulation involves the possibility of inaccurate VaR estimate. Longer historical sample periods, according to Mourtzis (2020), lead to reduced variability in the VaR estimate when the historical simulation is put into practice. When using the historical simulation technique, a there must be a compromise between extended sample time horizon, which may go against the predictions of a parametric model like GARCH or its observations, and short sample periods, which decrease the estimate's accuracy. According to the historical simulation technique, the forecast distribution can only experience risk factor change that match those seen during the historical sample period. When predicting "tail" the odds, such as the first, second, or fifth percentile, the problems can become more problematic because in those situations, the proportion of historical sample observations that reflect draws from the tail of the true distribution must be minimal and may even be very tiny. For example, when there are 200 observations, fewer than 59 data may have any effect on the estimation of the tail of the distribution.

For order statistics, standard errors may also be calculated, but only lengthy series can address the issue of portraying extremely large units rather than historically exceptional changes. Indirect evidence of the issue was identified by Mourtzis (2020), who employed the HS approach—a method for dealing with big samples and large units of data—to create significantly greater VaR estimates on average. Additionally, Taylor and Francis (2022) demonstrated that if the return distribution has a fat tail, historical simulation produces a VaR prone to upward bias and higher fluctuations. This was observed in a simulation research employing normal return distributions. He contends that the drawbacks of this strategy make it unsuitable for estimating tail values. A series of one thousand findings would permit only a few of 100 observations to considerably boost the representation of major changes and have an impact on tail estimate.

## 2.5 Advantages of measuring precision of estimated value at risk

It is challenging to evaluate the differences among short and long sample time horizons when using the HS method since it does not give birth to a statistical measure of precision. The capacity to quantify this accuracy or goodness-of-fit feature is really lacking in typical VaR models of all sorts, as Cavicchioli (2022) points out. He demonstrates how a rough estimate of the predicted VaR's variance might offer additional, helpful details regarding the estimation of VaR. Jorion (2016) advises that VaR be reported with confidence intervals at all times and demonstrates how incorporating the standard error of the VaR estimates might increase their effectiveness.

The problems mentioned by Cavicchioli (2022) might be resolved by measurement of the unpredictability in the projected VaR for an unknown return distribution. Hammersley J (2013) points out that a standard error may be calculated in a Monte Carlo VaR study. He advises creating a confidence range around the estimate from any VaR model using a Monte Carlo prediction land standard error. Unneeded assumptions about the distribution of portfolio returns are introduced by a parametric representation. For a nonparametric representation, the standard error must be boot-strapped from the sample observations set.

## 2.6 Empirical literature review

The most famous tools for assessing market risk is the historical simulation approach, many academics have employed it. Since the historical simulation approach takes a long time to respond to changes in the market and economic environment, the results may become stale over time. A brand-new VALUE-AT-RISK SEMIPARAMETRIC MIRRORED HISTORICAL SIMULATION MODEL is introduced to counter the flaws of the initial method. The Romanian Journal of Economic Forecasting emphasizes the significance of creating the best VaR methodology for assessing market risk in developing economies.

The employment of conventional VaR methodologies, particularly the filtered historical simulation approach and the linear historical simulation approaches, is discouraged or outlawed in favor of methods that can capture the heavy tails. However, since volatility is fluctuating over time, it is impossible to manage severe manifestation events and deficits that occur at the tail of the dispersion. Previous research has shown that nonparametric, hybrid, and parametric techniques may produce credible VaR estimates.

A study was undertaken by Muneer Shaik and Lakshmi Padmakumari in 2022 across three distinct time periods: the general term (from 2006 to 2021), the world economic recession of 2008 to 2009, and the covid phase from 2020 to 2021. The findings reflected that the exponentially moving weighted averages (EMWA) model beats the normal distribution and historical simulation estimate techniques each of the six stock indices throughout both crisis sample periods and the overall. According to the findings, VaR models perform badly when compared to the entire sample period at times of crisis like the GFC and covid 19. The results of the study also show that the forecasting accuracy of COVID-19 period VaR approaches is insufficient when compared to the time of the GFC.

The methods for computing VAR, HS, and filtered bootstrapping were changed in order to improve the quality of the results, which finally resulted in hybrids. The unique hybrid value at risk approach developed by Sasa Stepanov, Milena Cvjetkovi, and Nikola Radivojevi (2016) is depended on the (EVT) and calculates value at risk and expected shortfalls concurrently for high quantiles of return distributions. The method is effective in determining market risk in emerging markets. Hong et al (2014), Leptokurtosis, asymmetry, autocorrelation, and heteroscedasticity are some of the actual characteristics of returns in developing markets that are intended to be captured by this model. The investigators came to the conclusion that the strategy is intended to develop the innovations IID and to effectively capture changes in the chain of stock returns with markets that are emerging.

It also recognizes that the likelihood of the sudden reversals in developing markets is higher than what the normalcy assumption would imply. Leptokurtosis and asymmetry are successfully captured by the nonparametric half of the model, while the parametric portion of the model accurately catches the time-variable volatility. This approach is less computationally intensive than other approaches that also rely on a large number of estimated factors to effectively capture abnormal kurtosis and time-varying volatility, despite having the advantage of successfully capturing the strong dynamics in emerging market returns according to Asaf, 2015. It used the Monte Carlo testing approach.

Paul and Sharma (2017), and Fuentes et al. (2018) insinuates that the findings of the simulations shows that value at risk estimates derived from using this method may be relied upon, and that, in compliance with the Basel Committee's requirements, this method can be used dependably in the emerging markets. It was not possible to perform a simulation since no exceeding were discovered during the backtesting period for the market index BIRS for VaR estimations developed for the degree of trust of 99 percent. Therefore, it was recommended that future studies assess the validity of the enhanced approach utilizing a variety of backtesting approaches, rather than the usual AR(p)-GARCH (1,1) model, particularly for more severe (1 percent or less) VaR criteria.

Second, Tyson Clark (2019) of Utah State University investigated predictive distributions for financial risk management using Filtered Historical Simulation. His discovery was that he came to the conclusion that in order to compute the Var using filtered historical simulation, he first needed to estimate a Garch model to take volatility clustering partners into account. He then used the "RuGatch" optimizer to improve search parameters. The bootstrap procedure for the filtered historic simulation employed these settings. The parametric variables were optimized and then used for the bootstrap procedure for filtered historic simulation.

Tyson Clark's study (2019) came to the conclusion that there is a significant underestimation of the likelihood of an extreme loss in the VaR estimates derived from filtered historical simulation as compared to the predictions based on unadjusted volatility. This has been a concern for banks in the past since many of them have estimated VaR using solely historical returns, which implies that all potential future shocks to their portfolios have already happened. As fresh market failures, like the financial crisis of 2008, cause asset prices to drop rapidly, we can show that this is not a true assumption only in the previous few of decades.

The development of severe market risk metrics through time (Alexander, 2008; Aragones et al., 2001; Berk & DeMarzo, 2012; Clare et al., Dowd, 2005; Ellis, 2017). From the classic standard deviation of economic resources price returns to the more recent alternatives of value at risk and anticipated shortfall, the study along this broad subject indicates that the extreme market risk metrics have been upgraded over the past three decades.

With time, stop loss limits applied during market transactions were added to the restrictions of the naive SD estimator. Additionally, gap analysis looks at the difference in net income brought on by the sensitivity of assets and liabilities to interest rates. The first and second order mathematical derivatives of asset prices with changes in risk variables make up sensitivity measures as well. The terms "beta" for stocks, "duration" and "convexity" for bonds, and "Greeks" for options are some examples. Additionally, in terms of capital quantity, capital buffers like margin amount and risk capital indicate extremely high market risk. These methods were developed to mitigate the severe market losses and safeguard the reliability of the banking system, respectively.

This analysis reveals that a number of these extreme risk management strategies also function as means of absorbing and reducing the effects of high market risks. Notably, no estimate is perfect, and each solution has benefits and drawbacks. Nevertheless, all of the above-mentioned metrics primarily capture the effects of loss while also directly summarizing the likelihood (more specifically, the probability distribution) of loss.

VaR and the anticipated shortfalls that are probabilistically expressions of severe deficits, have overcome this significant constraint. The var is a tail quantile that depicts the likelihood limit for astronomical market losses. The average of losses larger than var is what the ES calculates. The ES is also known as the Conditional VaR (CVar) and the Expected Tail Loss (ETL).

According to Chen et al. (2012), Asai et al. (2012), and Abad et al. (2014), the conditional volatility model is not as accurate as the parametric distribution fitting of return distributions. Second, VaR-expected shortfalls estimate using the EWMA method is erroneous (Abad et al., 2014; Chen et al., 2012). The empirical results point to a generally equal prediction accuracy between the value at risk predictions that derived from the stochastic volatility (SV) family models and the GARCH family models, with a few small exceptions (Gonzalez Riveria et al., 2004). Migration from the GARCH framework to the SV technique does not result in any appreciable improvements (Chen et al., 2012).In general, it is observed that realized volatility (RV) models developed by Asai et al. (2012) and fractionally integrated—asymmetric power ARCH (FIAPARCH), which have long memories and leverage effects, produce extremely accurate prediction estimations of value at risk and expected shortfalls

even though an RV model is found to produce more accurate VaR estimates than a GARCH family model under a Gaussian distribution, Giot and Laurent (2003) and Brownlees and Gallo (2011) note that under skewed and leptokurtic distributions, such as the skewed (S)-t distribution, both competing frameworks produce comparable levels of VaR forecast accuracy. The second line of reasoning contends that the accuracy of the VaR and ES estimations significantly increases when asymmetric and fat-tailed distributions are taken into account:

In more detail, the symmetry requirement limits symmetric fat-tailed distributions like the student t distribution, which fits the data in the tails better than the Gaussian distribution. As a result, it may provide erroneous value at risk and expected shortfalls (Brooks and Persand, 2003) by underestimating probability mass in the left tails. The greatest losses are not limited by the t distribution, which might result in estimations of high risk that are deceptively low at higher confidence levels. As a result, estimations of tail risk based on t-distribution are erroneous. Additionally, the t-distribution is unstable, making it impossible to project value at risk estimations over a longer time horizon.

Also see backtesting extreme value theory models of the projected deficit by Alfonso Novales and Laura Garcia-Jorcano in Quantitative Finance (2019). Although the main barrier to this transformation has been the lack of straightforward methods for assessing the accuracy of expected shortfalls forecasts, the Basel Committee has stated that expected shortfalls produces better outcomes than VAR when evaluating market risk.

As a result, the expected shortfall was employed in this study, although it is challenging to carry out backtesting because Nikola Radivojevi's earlier (2016) study found that backtesting was unsuccessful. In order to backtest value at risk and projected deficit, various techniques were applied in this study. While the Basel regulations for VaR testing are predicated on counting the number of exceptions, choosing an ES model requires considering the extent of tail losses that extend beyond the VaR border. Alfonso Novales and Laura Garcia-Jorcano (2019) conducted the first in-depth assessment of a range of different ES backtesting methodologies that have been offered in the literature in recent years.

In 2017, Brandolini and Colucci introduced the bootstrap technique known as the Filtered Historical Simulation, using random sampling and re-sampling of standardized residuals from the first sample, with the parameters remaining constant across all bootstrap repetitions. They assert that this strategy does not take into account volatility clusters as a result of the IID assumption. Radivojevic et al. (2017) suggested a new Historical Bootstrap VaR model based on the concepts of Babu and Singh. An intriguing nonparametric model for VaR estimations was put out by Alemany et al. Their claim is supported by the kernel estimation of the cumulative distribution function after a twofold change.

However, rather than measuring market risk, the approach is more appropriate for gauging operations risk. Bee suggested the dynamic historical simulation model, which is quite similar to the FHS model provided by Fernandez, to capture heavy tails and heteroscedasticity in financial data. Although the research study only includes developed markets, the model performs exceptionally well at a very high degree of confidence.

Additionally, Abdelmageed, H. M., and Arabi, K. A. M. (2018). Modeling Value at Risk: Saudi Stock Market Evidence. utilizing nonparametric and parametric techniques supported by backtesting to estimate VaR and pick the optimum tool, Archives of Business Research, 6(6), 339–352. The research produced the following findings. The most widely used method for calculating value at risk, at least among businesses and banks, is the fundamental historical simulation. It is assumed that this refers to the routine, frequently fleeting, everyday return of zero. Its benefits include simplicity, adaptability, and independence from the complicated normalcy assumption.

Its main flaw is the requirement for lengthy time series, which calls for constant updating, as well as the risk of selecting extreme values. When this procedure was used to the TASI log return, it resulted in two estimates with different magnitudes and LR backtest acceptability. In addition to failing the LR test in comparison to the VaR 1 percent, its VaR 5 percent is approximately half that of the VaR 1 percent. It is intended that conditional value at risk will enhance VaR. It showed an almost two-fold VaR % as compared to a straightforward historical simulation, however it failed the LR test. The percentile method mimics historical simulation.

The experimental quartile has similar benefits to the above approaches, but it has disadvantages such as its reliance on the assumption that the returns distribution is constant and its inefficiency when p is near to zero. However, it turned out to be the only technique that passed the backtest at both levels. Thus, it may be said that bootstrapping simulation is an advancement above traditional historical simulation. In comparison to Monte Carlo, the losses were the worst.

In order to get estimates that may be utilized to quantify and foretell market risk, Degiannakis et al. (2012) examined the performance of three distinct VaR models. They found proof that widely accepted approaches deliver reliable VaR estimations and forecasts during financial crises Letic and Miletic (2015) look at value-at-risk (VaR) model performance during the world economic crisis in a few new capital markets in Central and Eastern Europe (CEE). When compared to GARCH-type models with normal distribution, historical simulations, and risk metric methodologies, backtesting research for the crisis shows that GARCH-type models with t-distribution of residuals produce higher VaR estimates.

Su et al. (2010) discovered that the historical simulation value at risk estimate model outperforms the GARCH (1, 1) - AR (1) model significantly at a 95% level of confidence. Ramalho (2020) used historical simulation, GARCH (1,1), and dynamic extreme value theory-POT to determine VaR for the countries of the, the United Kingdom, Portugal, France, Italy, Germany, China, Spain, and United States from January 1, 2007, through August 31, 2020. It was shown that market volatility increased along with the number of fatalities throughout the COVID-19 era; the majority of exceedances take place under crisis conditions as opposed to routine ones. Omari et al. (2020) forecasted the VaR of financial markets during the COVID-19 time period using conditional extreme value theory.

Additionally, studies using the historical simulation (HS) method, such as those by Vlaar 2000, Jackson et al. (1997), and Hendricks (1996), found that VaR estimates obtained from HS performed better than those using Gaussian methods. These publications highlight possible benefits of the HS strategy. First, the empirical distribution allows for fat tails. Second, no distributional assumption offers the theoretical flexibility required to be applied to derivatives. Third, HS is conceptually simple and comprehensible. Our third argument is that the procedure is straightforward to use and the results are straightforward to display. It is straightforward to generate confidence intervals for (non-parametric) value at risk and expected shortfall calculations. Huang and Tseng (2009) discovered that the historical simulation value at risk was marginally more reliable than the MCS value at risk. Although estimates at high confidence levels that represent the tails (rare occurrences) have a significant standard error, the HS estimator is not exact. HS estimations are very challenging to confirm.

When compared to HS, Kernel smoothing, and CaViaR techniques, CS VaR estimates are shown to yield estimates that are significantly erroneous (Huan, Lin, Chien, and Lin, 2004; Bao et al., 2006). This is true even if backtesting studies (Pritsker,1997; Bao, Lee, and Saltoglu, 2006) show that MCS VaR estimates perform better than Gaussian VaR estimates. According to Abad et al. (2014), it performs worse than the HS and (parametric) student t approaches. These studies demonstrate how much more exact and cautious the EVT methodology is than the MCS method. The inadequacies in the traditional methodologies and the need to properly identify the high market risk were the driving forces behind the creation of alternative VaR-ES assessment methodology.

Reviewing studies that looked at both conventional approaches and those that used alternative techniques strongly suggests that precise estimation of extreme market risk becomes more crucial because it is frequently challenging to simulate unforeseeable circumstances that are typically not included the scope of observations available.

The GARCH-GED approach for VaR estimation is superior to the GARCH-N model and the HS-(ARMIA prediction), claim Fan et al. (2008). Furthermore, according to Bali and Theodossiou (2007), the VaR measures from the GARCH-SGED model outperform those from the GARCH-GED model and GARCH-skewed t model in statistical backtesting, but the VaR measurements from the generalised t model are less accurate. The GARCH-SGT model outperforms the GARCH-SGED model in terms of VaR and ES estimations, though. According to Lee et al. (2008), the GARCH-SGED model is superior to the GARCH-GED model for assessing severe market risk. According to a study on real estate markets by Zhou and Anderson (2012), the implied VaR estimates from the FHS process and the VaR estimates obtained under the assumption that the extreme values of the GARCH process filtered residuals follow the GP distribution do not seem to be any more accurate than those from the GARCH type GED process.

On the other hand, according to Angelidis et al. (2004), the GARCH, exponential (E)-GARCH, and threshold (T)-Generalized AutorRegressive Conditional Heteroskedasticity models with t-distributed innovations beat their GED counterparts in backtesting. The EGARCH-t and AP-ARCH-t models can enhance the leverage impact or volatility asymmetry in place of the GARCH-t model. Su and Knowles (2006) show that the VaR and ES estimates are only marginally more accurate than the GED and SGED across the student t distribution. In fact, according to Bali et al. (2008), the GED VaR may significantly underestimate market risk.

Additional information on "t" skewed distribution was learned from this review, including the following:

1. Studies that are favourable: According to Giot and Laurent (2003), estimates based on the VaR and ES predictions of the skewed t distribution are more accurate than those based on the gaussian and student-t distribution assumptions. According to Altun et al. (2018), the skewed t distribution provides more accurate VaR estimations than the skewed N distribution. It also demonstrates that the backtesting efficiency of the skewed t VaR-ES models is on par with that of the GED and the SGED.
2. Unpopular studies: According to Angelidis and Degiannakis (2005), capturing the leverage impact or volatility asymmetry is more important to accurate conditional VaR estimates than the return distribution. According to Corlu et al. (2016), the generalized lambda (GL) distribution is preferable than the skewed-t distribution.

The effectiveness of unconditional and conditional EVT models has been compared and assessed in a small number of researches. These are Bystrom (2004), Kuester et al. (2006), Marimoutou, Raggad, and Trabelsi (2009), Zikovic and Filer (2013), Danielsson and De Vries (2000), and Samuel (2008). The vast majority of these studies support the notion that VaR and ES estimations generated from conditional GEV and GPD are superior to those obtained from unconditional GEV and GPD in terms of prediction accuracy. According to Bystrom (2004), the conditional estimates have little changed. The Markov Switching (MS) ARCH method can significantly improve the performance of statistical backtesting, according to Samuel (2008). Additionally, Filer and Zikovic (2013) discover that value at risk estimates produced from GPD perform just slightly better than those calculated using the FHS technique.

According to Tesfalidet, Desmond, Hailu, and Singh (2014), uncorrected CF VaR and ES estimates can be non-monotonic, i.e., the extreme tails may provide lower values. In a mathematical and simulation-based line of research that started with Jaschke (2002), the origins of non-monotonicity are investigated. According to Christoffersen (2003) and Giamourdis and Ntoula (2009), the CF VaR is monotonic and well-behaved when the skewness and kurtosis parameters in the CF expansion formula are inside their limited domains of validity (DVs). The DV of the skewness coefficient ranges from -1.2 to +1.2.

The (non-monotonic) shortcomings have been overcome by statistical innovations, which now offer incredibly accurate risk predictions. Chernozhukov, Fernandez-Val, and Galichon (2010) provide a formula for increasing rearrangement to solve the problem of the narrowness of the DV for the CF formula. Later, Maillard (2012) points out that the majority of studies confuse the linked empirical data with the skewness and kurtosis parameters in the CF expansion. The formula coefficients can be calculated using sample estimates that satisfy the DV, as is suggested in the approach. Amedee-Menasme, Fabric, and Maillard (2019), who provide analytical formulations for a range of empirical Skewness and Kurtosis values, further enhance this extraction. Polynomial regressions with the Response Surface Methodology (RSM) are used to produce the analytical equations.

While the VaR-ES forecasts using the traditional symmetric absolute value (SAV) version of the CQ approach are accurate in calm markets/phases, the accuracy declines during market volatility, as noted by Bao et al. (2006) and Polanski and Stoja (2010). However, the forecast accuracy during market volatility increases dramatically when using asymmetric extensions of the CQ technique that take into account the leverage effect and other non-linearities of returns, especially at high confidence levels. Asymmetric versions that increase the precision of VaR and ES estimates include the asymmetric slope (AS), Indirect GARCH (1, 1) (IG), combination of T-GARCH and Wong and Li's Mixture ARCH model (Yu Li, and Jin, 2010), and the non-linear dynamic quantile (NLDQ)-AS extension (Gerlach, Chen, and Chan, 2011; Sener et al., 2012).

The (EVT) extreme value theory is a solid framework that may be used to describe and forecast low frequency high severity (LFHS) events in the field of probability theory. According to Wong (2013), the EVT framework has been utilized in risk measurement to evaluate operational risk and optimize portfolios. One of the key benefits of the EVT is that it can specify the tails of the returns distribution while not interfering with distribution-wide modelling. Since the true distribution of the returns is unknown, only empirical distribution, parametric density, and semi-parametric approaches may be used to approximate it.

To elaborate, providing the relevant assumptions are true, the tools of extreme value theory may be used to describe the extreme realizations of a certain random process or distribution. By showing that one of the three extreme value distributions—generalized extreme value (GEV), generalized logistic (GL), or generalized Pareto (GP)—can and frequently does converge to the asymptotic distribution of the appropriately scaled extreme realizations within a random sample from most distributions, Fisher and Tippett (1928) laid the foundation for EVT. This important discovery makes it possible to estimate the VaR and ES measures for the extreme quantiles without taking into account the specific characteristics of the whole distribution of returns.

The idea is that by describing losses as a few of large ones rather than a number of smaller ones, it will be less likely that value at risk and anticipated deficits would be underestimated. The former is more crucial in order to protect investment assets. This flexibility is further enhanced by the ability of the extreme value theory to independently represent the right and left tails of the asset return distributions. Embrechts et al. (1997) and McNeil et al. (2005) are cited as comprehensive and well-organized sources for the extreme value theory and its application in finance in a number of the publications in the extreme value theory strand of literature that have been examined.

## 2.7 Chapter Summary

This chapter has broadly explained the components of modelling the market risk using bootstrapping and filtered historical simulation. Findings from various researchers which used same methods and also from those who employed different methods formed part of this chapter and their varying conclusions were drawn.

# CHAPTER lll

 **Research Methodology**

##  3.1 Introduction

Because financial data is not routinely dispersed in an independent and identical manner, it can be difficult to account for periods of volatility when something like the 2008 financial crisis happens. When bootstrapped in a filtered historical simulation, the asymmetric GARCH model allows for this volatility clustering pattern and will offer more accurate Value at Risk measurements to financial institutions trying to remain compliant with the 10-day, 1% significance Value at Risk limits stipulated by Basel II rules. This chapter demonstrates model that financial institutions have begun to utilize in order to comply with Basel 2 criteria. Basel II requires banks to analyze their risk at the 99 percent significance level using internal Value at Risk models. Banks must also calculate possible losses over a 10-day risk horizon. This research is desk based since every information for quantifying market risk for any organization, that is listed on the stock exchange can be obtained from Yahoo finance portal.

## 3.2 Research Design

The research design used in this analysis is an explanatory research design that tries to explore how value at risk, also known as market risk, affects enterprises in Zimbabwe. The study employs a quantitative research strategy as well as secondary data from other sources. The data that will be used in the study is readily accessible from Google Yahoo finance.

## 3.3 Justification of the Research Design

The data that is used on this research can be accessed through the Internet making use of search engines such as Yahoo Finance. In case of quantitative data, the use of secondary data analysis saved time that was spent collecting data. Higher and larger quality databases that would not be easily obtained by the researcher on their own are also provided. Census data, information gathered by government agencies, company records, and data that was initially gathered for other research goals are all common sources of secondary data for social science. In addition, social and economic change experts view secondary data as crucial because it is impossible to perform a fresh poll that can accurately capture historical change and/or advancements.

## 3.4 Research Methodology

Research, according to Ranjit (2017), is a way of thinking that entails understanding and constructing guiding principles that govern a certain approach as well as developing and putting to the test new ideas for the growth of your career. The research was carried on the problem topic utilizing both quantitative and qualitative techniques.

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| --- |
| Bootstrapping  |

|  |
| --- |
| Portfolio daily equity returns analysis |

|  |
| --- |
|  F.H .S(filtered historical simulation) |

|  |
| --- |
| Unpredicted losses due to market risk |

|  |
| --- |
| Evaluation of systematic risk  |

|  |
| --- |
|  V. A. R(value at risk) |

|  |
| --- |
| Lucrativeness, profitability |

#### Figure 3.1

The analysis of market risk emerges vital and considered due to the losses which are generated by the firms due to risks that are not forecasted. This task of predicting the risk was done through evaluation of daily equity returns of a portfolio as time pass by. The zeal to know and make well informed decisions accordingly will lead to bootstrapping and filtered historical simulation methodologies.

## 3.5 Model Specification

Filtered historical simulation is a semi-parametric method that combines empirical non-normal return distributions obtained from historical data with Monte Carlo simulation. This solves many of the problems associated with basic historical simulation by allowing it to calculate an h-day VaR when h is more than a few days. Because it is a non-parametric model, it will not account for the present market volatility (Alexander 2016). By combining an estimated EWMA model with the i-.i.d. Bootstrap, filtered historical simulation yields this semi-parametric model. This enables the model to account for value correlations while without limiting them over time. The EWMA process that underpins this filtered historical simulation evolved from Robert Engle's 1995 less complex auto-regressive conditional heteroskedasticity (ARCH) model. Enders, (2018) goes into great length on the GARCH model and filtered historical simulation. The model was created to account for volatility clustering patterns, which are common in financial data that can encounter market shocks such as bubbles, and where a model assuming constant variance would be incorrect.

## 3.6 Historical Simulation

Simulations based on historical data one of the criticisms leveled with Delta Normal is its reliance on normal distribution (Taylor, 2019). The historical simulation is offered to spare the VaR calculations from such a significant assumption. The examination of the histogram of the monthly loss and profits serves as the foundation for the historical simulation. Under the entire loss and gain histogram:

 VaRα = Percentile (RP F, t+1−n) mn=1, 100 ∗ α

Benihashemi, Shokooef and Sarah Navidi (2017) averred that, the idea behind historical simulation is that one must look to the past in order to anticipate the future of an asset. The history of the business would not be revealed by any of the assets. Because of this, it assumes that what occurred will happen again and that we must look to the past in order to predict the future. The historical simulation's first fault is its significant reliance on the past, and it is limited to what happened in the past. It cannot cross that line. Also, when VaR estimate is taken into account, the significance of each observation is the same. The filtered and weighted simulation approaches are provided to overcome such formidable obstacles.

## 3.7 EWMA filtered historical simulations

Barone-Adesi, Giannopoulos, and Vosper (1999) initially developed the concept of filtered historical simulation. It is an excellent approach for calculating VaR for portfolios since it builds the predictive density that the portfolio may utilize for several days in the future using both nonlinear econometric models and historical returns. Filtered historical simulation risk estimates are generated directly from the tails of the distribution as opposed to conventional models, which have the issue of underestimating the risk of extreme events.

According to Harper (2022), exponentially weighted moving averages Filtered historical simulations (EWMA FHS) is a more sophisticated and realistic model, the volatility filtered model, which corrects the observation depending on its volatility. As an observation series' volatility rises, its value as the final observation increases. Given that VaR and volatility are related, VaR estimation makes sense when using volatility filtering. Two well-known methods are GARCH estimations and EWMA. A data collection that contains time series error terms that either fit into the ARCH/GARCH family or follow the GARCH/ARCH method is required for GARCH/ARCH estimates. That is a rather optimistic projection, and it is not always accurate. In the 100 research, discovered that more than 17% of the return series (with linked time series) used the ARCH/GARCH filtering method. Therefore, the EWMA filtering is preferred over them. A statistical technique called EWMA (exponentially moving average) carefully examines the most recent data since recent findings are more useful than previous ones. It is a way of estimating volatility. Such a method is predicated on the idea that today's return and volatility determine the volatility of tomorrow Gurrola –Perez and Murphy (2015). f (t + 1) (t, Rt).To integrate them, the model requires a number known as the decay factor that has a linear model.

 σt+1 = k ∗ σt + (1 − k) ∗ Rt

Rt: (t-day Return of the information or asset.), the factor k is also known as the decay factor which is globally agreed to be 0.94 (Harper, 2022). With regard to its volatility estimates, the data must be revalued, thus;

 RLt = (σt/σt−1) ∗ Rt

Where R't is the t-day return's rectified or filtered return. As a result, the value of the observation also increases as the volatility does. After all returns have been adjusted for volatility, the widely used historical technique has been used, and the associated Value at Risk has been computed. As can be seen, the EWMA process is an intermediary step in which the returns that the portfolio bears are corrected. Abad et al, (2014) insisted that, when analyzing volatility, the approach is remarkably independent of distributions and helps researcher to arrive at conclusions that go beyond its historical context. Because of the filter process and volatility consideration, it can swiftly adjust to changing market circumstances. Also, it prioritizes the most current data.

The problem that percentiles in the tails of observed return distributions were not well defined by simple functional forms like the normal distribution or, in some cases, by the returns in the model data windows, led to the development of filtered historical simulation techniques. Models of historical simulation react to variations in conditional volatility. We must modify our estimates of value at risk to account for changes in conditional volatility. The most fundamental approach, which is at the core of the idea of filtered historical simulation, is to estimate the new conditional volatility and use it to scale the returns used for VAR computation. The study reveals the qualities of the data by applying the EWMA calculation techniques, which results in the computation of volatilities in the market to assess risk Chakraborty et al, (2021).

## 3.8 Bootstrapping

 The bootstrap technique uses resampling to sample a dataset and replace the data in order to estimate a population's basic statistics. According to Bland, J.M., and Altman, D.G (2015) to estimate statistics like the mean and standard deviation, the method is used. The goal of bootstrapping is to make inferences about a population from sample data (there is a clear connection between sample and population). This is done by resampling the sample data and inferring information about the sample from the resampled sample of data. The actual inaccuracy in a sample statistic is unknown since we don't know the population.

Lyons, Mitchell B et al, (2018) states that, the difficulty starts here because with bootstrap resampling, the 'population' becomes the sample and this is known; as a result, the accuracy of inferring the 'real' sample from resampled data becomes measurable. The initial phase of the bootstrapping approach is the extraction of the necessary number of data from the data collection, disregarding any limits. Flowing from that bucket, the VaR is computed using any approach, including historical simulation or delta normal. The delta normal is favored in study since there is no historical value. As a result, the delta normal is used for the bootstrapped data. Up until the day of analysis, the total number of observations obtained from the data set is kept as half of the total number of observations Gargliardini et al, (2018).

## 3.9 Chapter Summary

This chapter demonstrated a model that financial institutions have implemented in order to comply with Basel ll criteria. The models that are to be adhered to are bootstrapping, historical simulation and filtered historical simulation. The model which assumes constant variance in financial data is a misrepresentation, for this will not happen considering the dynamism of the market. The GARCH model and filtered historical simulations are implemented so as to account for volatility clustering patterns. The idea behind historical simulation is that one must look to the past in order to anticipate the future of an asset. The past patterns of the business would not be betrayed by any of the assets. The historical simulation is offered to spare the value at risk calculations from such a significant assumption. In a bid to overcome such formidable obstacles, the filtered and weighted simulation approaches are introduced.

# CHAPTER IV

**DATA PRESENTATION, ANALYSIS AND DISCUSSION**

## 4.0 Introduction

The empirical findings and their interpretation are presented in this chapter. The measurement of variables, model specification, data consistency, statistical and economic relevance of variables in the analysis, number of observations, and the fact that all significant variables are included in the analysis all play a significant role in the econometric study's strength. Market risk was measured using bootstrapping and filtered historical simulation. An assessment of how market risk and volatility go hand in hand will be examined where volatility is accounted for under EWMAs as well as to numerically illustrate the measures. Value at risk under parametric circumstances will be calculated and explained for data that belongs to Old Mutual Ltd.

## 4.1 Volatility and market risk

The standard deviation is the main metric of volatility that analysts and traders utilize. This metric displays the typical deviation of a stock's price from the mean over time. Volatility is a significant factor that is the focus of risk management strategies since it is virtually always forecasted and used to gauge risk in credit institutions.

 Volatility is not constant and changes over time for many models. In its simplest form, volatility is a measurement of how much prices vary. If a stock price fluctuates widely, experiences abrupt highs and lows or otherwise exhibits unpredictable behavior, it is said to be highly volatile. Volatility should be approximated from data since it is an unobservable fact.

The fig.1 below shows a trend of adjusted stock prices for Old Mutual from January 2020 to January 2023;

#### Figure 4.1 stock prices trends

Every financial organization, including banks, has been their financial landscapes change as a result of the crisis. Impact on market risk includes a break in the conventional risk management strategy, Models are no longer effective in forecasting stress events owing to spikes in volatility, asset-price uncertainty, ineffective hedging behavior, significant ratings downgrades that result in an indirect deterioration of portfolio quality, and pressure on net interest margins. For the investment, borrowing, and derivatives portfolio, the distorted and illiquid market circumstances have produced valuation issues.

The stock prices are adjusted for dividends and stock splits hence the name ADJ close. The ability to foresee the volatility of the financial markets is a valuable characteristic that has numerous applications in risk management. The inherent risk of a stock with a high amount of volatility is greater, but the risk is symmetrical. When making an investment in a volatile security, both the chances of success and the risk of failure increase. As a result, a lot of traders with high risk tolerance rely on a range of volatility metrics to make trading decisions.

 The daily stock returns are used to quantify volatility. Fig 2 below shows a trend for returns that are not constant which reflects volatility;

#### Figure 4. 2 Volatilities in returns

Returns volatility has some clustering; as a result, it is auto-correlated. The finding that price changes tend to follow each other in cycles of large and small changes, respectively. Filtered historical simulation is used because EMWA was used to filter the volatility pooling in the data that was used to represent market risk.

Volatility calculation was done in excel; the table below shows the calculation where the weights are decreasing as the data gets older. The adjusted volatility in EWMA model was obtained as followed:



Table 4.1 EWMA Model

Unadjusted volatility that is calculated using the historical standard deviation method, which gives even or equal weights to daily changes in returns is highlighted in red. The volatility in green is calculated under EWMAs which gives more weights to the most recent data. The last day of the analysis’ return (01/31/2023) has the highest weight that is 0.06 and that is giving more importance on what recently occurred to determine tomorrow’s volatility. The weights are decreasing exponentially as the data gets old. The method’s concept is that what recently occurred is a reflection of current market conditions or is likely to happen tomorrow. The historical standard deviation method tends underestimate volatility as shown by the figures in the table above. The 2.2565% implies that the returns are swinging from the daily average return by 2.2565%. The higher the volatility the greater the market risk. The moving average of asset values, including those of stocks and commodities, is frequently calculated in finance using EWMA. To track a process's effectiveness over time, it is also used in quality control. The book "Forecasting: Principles and Practice" by Rob J. Hyndman and George Athanasopoulos (2018) is one of the most often used references for exponentially weighted moving averages. The book goes into great detail on EWMAs and how they are used in time series forecasting.

As volatility rises, VaR will also rise. Investors will therefore attempt to alter their portfolio's diversification by reducing the proportion of those assets whose volatility is expected to rise. Volatility is a crucial criterion for determining the kind of options that should be purchased or sold. Volatility variations can affect the pricing of the equilibrium assets. Therefore, whoever could predict volatility changes more accurately would be in a better position to be able to manage market risk.

## 4.2 Value at Risk under Parametric circumstances.

This approach uses a theoretical probability distribution similar to the normal to make approximations about the potential movement of the portfolio. To determine value at risk using the parametric technique, we require only a few values, namely:

1. Portfolio value
2. Expected volatility
3. Time horizon
4. Confidence level

Old mutual has subsidiaries such as Central African Building Society (CABS bank), the price drops affect the banks’ equity position. The VaR shows the worst-case scenario for a given period for which under the Basel Committee rules set the period at 10 day i.e. banks are required to calculate market risk over a 10-day time horizon. The value at risk will show the maximum a bank can lose if things go wrong on the financial market.

The diagram below shows returns from January 2020 to January 2023 that are normally distributed;

 

#### Figure 4.2 Logarithmic returns

The calculation of value at risk under parametric circumstances was performed in excel as shown below:

|  |  |  |
| --- | --- | --- |
|  | Portfolio Value | $2,440,000,000 |
|  | Expected Volatility | 0.0071600% |
|  | Time(days) | 10 |
|  | Confidence level | 0.95 |
|  | Stress Event | 1.644853627 |
|  |  |  |
|  | VaR | $32579.20 |

#####  Table 4.2 Value at risk 95% confidence level

|  |  |  |
| --- | --- | --- |
|  | Portfolio Value | $2,440,000,000 |
|  | Expected Volatility | 0.0071600% |
|  | Time(days) | 10 |
|  | Confidence level | 0.96 |
|  | Stress Event | 1.750686071 |
|  |  |  |
|  | VaR | $34675.39 |

#####  Table 4.3 Value at risk 96% confidence level

|  |  |
| --- | --- |
| Portfolio Value | $2,440,000,000 |
| Expected Volatility | 0.0071600% |
| Time(days) | 10 |
| Confidence level | 0.97 |
| Stress Event | 1.880793608 |
|  |  |
| VaR | $37252.40 |

#####  Table 4.5 Value at risk 97% confidence level

|  |  |
| --- | --- |
| Portfolio Value | $2,440,000,000 |
| Expected Volatility | 0.0071600% |
| Time(days) | 10 |
| Confidence level | 0.98 |
| Stress Event | 2.053748911 |
|  |  |
| VaR | $40678.07 |

##### Table 4.6 Value at risk 98% confidence level

|  |  |
| --- | --- |
|  |  |
| Portfolio Value | $2,440,000,000 |
| Expected Volatility | 0.0071600% |
| Time(days) | 10 |
| Confidence level | 0.99 |
| Stress Event | 2.326347874 |
|  |  |
| VaR | $46077.37 |

##### Table 4.7 Value at risk 99% confidence level

From the above tables showing value at risk under different confidence levels, the bank needs to or they have to check if they have enough equity to absorb such a loss. If the bank has enough equity, they will not lose any sleep. If they do not have enough equity, the bank needs to sell part of the trading portfolio to reduce the risk exposure Jorion (2019).

The timeframe is short i.e. 10 days, the assumption is that the bank can always sell tradable instruments on the financial markets and this will reduce their exposure. Old Mutual in Zimbabwe has diversified they have properties for rentals and also the bank thus they can manage market risk very well through implementation of Var.

## 4.3 Bootstrapping and Filtered historical simulation

From the Portfolio, logarithmic return series also known as geometric or returns that are continuously compounded from the daily returns of the portfolio taking into account weights. Despite the fact that the portfolio returns are logarithmic, the portfolio return series is created by first converting the individual logarithmic returns to arithmetic returns i.e. price change divided by initial price even though the portfolio returns are logarithmic. After that, the portfolio’s arithmetic return is calculated by weighing the arithmetic returns, before being converted back to the portfolio logarithmic return. The repeated conversions don’t make much of a difference with daily data and a short VaR horizon like the recommended 10- day VaR but over a longer time periods, the difference could be sizable. Chen and Gerlach (2019) supports this finding in a comparative study forecasting with filtered historical simulation.

The observations must be roughly independent and evenly distributed (independent and identically distributed) in order to use the bootstrapped Filtered historical simulation approach. Filtered historical simulation where volatility was accounted for in returns through use of exponentially weighted moving averages was performed in excel as shown below:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Date | Adj Close | Daily return u*i*  | Daily squared return u2*i* | Weighting (k=94%) | K\* u2*i* |
| 31/1/2023 | 52.36205 | 0.90827% | 0.008250% | 0.06 | 4.94974E-06 |
| 30/1/2023 | 52.83981 | 1.43629% | 0.0206293% | 0.0564 | 1.16349E-05 |
| 27/1/2023 | 53.60422 | -2.52721% | 0.0638679% | 0.053016 | 3.38602E-05 |
| 26/1/2023 | 52.2665 | -1.10295% | 0.0121650% | 0.04983504 | 6.06245E-06 |
| 25/1/2023 | 51.6932 | 0.91996% | 0.0084633% | 0.046844938 | 3.96465E-06 |
| 24/1/2023 | 52.17095 | 0.72994% | 0.0053281% | 0.044034241 | 2.3462E-06 |
| 23/1/2023 | 52.55316 | -1.28090% | 0.0164071% | 0.041392187 | 6.79127E-06 |
| 20/1/2023 | 51.8843 | -0.18433% | 0.0003398% | 0.038908656 | 1.32201E-07 |
| 19/1/2023 | 51.78875 | -0.36968% | 0.0013667% | 0.036574136 | 4.99844E-07 |
| 18/1/2023 | 51.59765 | 0.73801% | 0.0054466% | 0.034379688 | 1.87254E-06 |
| 17/1/2023 | 51.97985 | 1.64087% | 0.0269246% | 0.032316907 | 8.70118E-06 |
| 16/1/2023 | 52.83981 | -1.27391% | 0.0162284% | 0.030377892 | 4.92985E-06 |
| 13/1/2023 | 52.17095 | 0.36564% | 0.0013369% | 0.028555219 | 3.81754E-07 |
| 12/1/2023 | 52.36205 | -1.28560% | 0.0165277% | 0.026841906 | 4.43634E-06 |
| 11/1/2023 | 51.6932 | 0.00000% | 0.0000000% | 0.025231391 | 0 |
| 10/1/2023 | 51.6932 | 2.01288% | 0.0405168% | 0.023717508 | 9.60957E-06 |
| 9/1/2023 | 52.74426 | -4.06711% | 0.1654135% | 0.022294457 | 3.6878E-05 |
| 6/1/2023 | 50.64213 | 0.18850% | 0.0003553% | 0.02095679 | 7.44635E-08 |
| 5/1/2023 | 50.73768 | 0.75047% | 0.0056321% | 0.019699383 | 1.10949E-06 |
| 4/1/2023 | 51.11989 | -2.65168% | 0.0703138% | 0.01851742 | 1.30203E-05 |
| 3/1/2023 | 49.78217 | -2.33019% | 0.0542980% | 0.017406374 | 9.45132E-06 |
| 30/12/2022 | 48.63556 | 1.75272% | 0.0307202% | 0.016361992 | 5.02644E-06 |
| 29/12/2022 | 49.49552 | 0.19287% | 0.0003720% | 0.015380272 | 5.72127E-08 |
| 28/12/2022 | 49.59107 | -1.35793% | 0.0184398% | 0.014457456 | 2.66592E-06 |
| 23/12/2022 | 48.92221 | 0.38987% | 0.0015200% | 0.013590009 | 2.06566E-07 |
| 22/12/2022 | 49.11332 | -0.78126% | 0.0061036% | 0.012774608 | 7.79713E-07 |
| 21/12/2022 | 48.73111 | -2.98530% | 0.0891202% | 0.012008132 | 1.07017E-05 |
| 20/12/2022 | 47.29784 | -0.81137% | 0.0065831% | 0.011287644 | 7.43082E-07 |
| 19/12/2022 | 46.91563 | -7.61467% | 0.5798318% | 0.010610385 | 6.15224E-05 |
| 16/12/2022 | 43.47579 | 3.24353% | 0.1052049% | 0.009973762 | 1.04929E-05 |
| 15/12/2022 | 44.90906 | 2.00112% | 0.0400450% | 0.009375336 | 3.75435E-06 |
| 14/12/2022 | 45.8168 | 0.62370% | 0.0038900% | 0.008812816 | 3.42819E-07 |
| 13/12/2022 | 46.10345 | -3.05127% | 0.0931023% | 0.008284047 | 7.71264E-06 |
| 12/12/2022 | 44.71796 | 2.21879% | 0.0492304% | 0.007787004 | 3.83357E-06 |
| 9/12/2022 | 45.72125 | 4.79439% | 0.2298618% | 0.007319784 | 1.68254E-05 |
| 8/12/2022 | 47.9667 | 0.39762% | 0.0015810% | 0.006880597 | 1.08784E-07 |
| 7/12/2022 | 48.1578 | -0.79682% | 0.0063492% | 0.006467761 | 4.10652E-07 |
| 6/12/2022 | 47.7756 | -1.10610% | 0.0122345% | 0.006079696 | 7.43819E-07 |
| 5/12/2022 | 47.25007 | -1.42569% | 0.0203258% | 0.005714914 | 1.1616E-06 |
| 2/12/2022 | 46.58121 | -0.41111% | 0.0016901% | 0.005372019 | 9.07915E-08 |
| 1/12/2022 | 46.3901 | 12.65555% | 1.6016301% | 0.005049698 | 8.08775E-05 |
| 30/11/2022 | 52.64871 | -1.64688% | 0.0271221% | 0.004746716 | 1.28741E-06 |
| 29/11/2022 | 51.78875 | -0.74075% | 0.0054871% | 0.004461913 | 2.44828E-07 |
| 28/11/2022 | 51.40654 | -0.37244% | 0.0013871% | 0.004194198 | 5.81775E-08 |
| 25/11/2022 | 51.21544 | -0.56128% | 0.0031503% | 0.003942546 | 1.24203E-07 |
| 24/11/2022 | 50.92878 | 3.50267% | 0.1226869% | 0.003705994 | 4.54677E-06 |
| 23/11/2022 | 52.74426 | 1.26014% | 0.0158795% | 0.003483634 | 5.53185E-07 |
| 22/11/2022 | 53.41312 | -4.38827% | 0.1925693% | 0.003274616 | 6.3059E-06 |
| 21/11/2022 | 51.11989 | 2.03522% | 0.0414211% | 0.003078139 | 1.275E-06 |
| 18/11/2022 | 52.17095 | -4.87901% | 0.2380476% | 0.002893451 | 6.88779E-06 |
| 17/11/2022 | 49.68662 | 0.76629% | 0.0058720% | 0.002719844 | 1.59709E-07 |
| 16/11/2022 | 50.06883 | 0.57089% | 0.0032591% | 0.002556653 | 8.3325E-08 |
| 15/11/2022 | 50.35548 | 2.99087% | 0.0894531% | 0.002403254 | 2.14979E-06 |
| 14/11/2022 | 51.8843 | 0.73395% | 0.0053868% | 0.002259059 | 1.21692E-07 |
| 11/11/2022 | 52.2665 | -2.03146% | 0.0412685% | 0.002123515 | 8.76342E-07 |
| 10/11/2022 | 51.21544 | -0.93722% | 0.0087837% | 0.001996104 | 1.75333E-07 |
| 9/11/2022 | 50.73768 | -2.28581% | 0.0522491% | 0.001876338 | 9.80369E-07 |
| 8/11/2022 | 49.59107 | 2.28581% | 0.0522491% | 0.001763758 | 9.21547E-07 |
| 7/11/2022 | 50.73768 | -1.70944% | 0.0292218% | 0.001657932 | 4.84477E-07 |
| 4/11/2022 | 49.87772 | -5.21003% | 0.2714440% | 0.001558456 | 4.23034E-06 |
| 3/11/2022 | 47.34562 | 0.90408% | 0.0081736% | 0.001464949 | 1.19739E-07 |
| 2/11/2022 | 47.7756 | -1.30853% | 0.0171226% | 0.001377052 | 2.35787E-07 |
| 1/11/2022 | 47.15451 | -0.20283% | 0.0004114% | 0.001294429 | 5.32522E-09 |
| 31/10/2022 | 47.05896 | 0.80890% | 0.0065433% | 0.001216763 | 7.96161E-08 |
| 28/10/2022 | 47.44117 | -0.91048% | 0.0082897% | 0.001143757 | 9.48141E-08 |
| 27/10/2022 | 47.01119 | 1.41274% | 0.0199582% | 0.001075132 | 2.14577E-07 |
| 26/10/2022 | 47.68005 | -3.56999% | 0.1274480% | 0.001010624 | 1.28802E-06 |
| 25/10/2022 | 46.0079 | -0.93898% | 0.0088167% | 0.000949987 | 8.37579E-08 |
| 24/10/2022 | 45.57792 | 3.19780% | 0.1022593% | 0.000892987 | 9.13162E-07 |
| 21/10/2022 | 47.05896 | -1.02042% | 0.0104126% | 0.000839408 | 8.74038E-08 |
| 20/10/2022 | 46.58121 | 1.32452% | 0.0175436% | 0.000789044 | 1.38427E-07 |
| 19/10/2022 | 47.20229 | -0.81302% | 0.0066099% | 0.000741701 | 4.9026E-08 |
| 18/10/2022 | 46.82008 | 0.61038% | 0.0037257% | 0.000697199 | 2.59752E-08 |
| 17/10/2022 | 47.10674 | -5.95476% | 0.3545918% | 0.000655367 | 2.32388E-06 |
| 14/10/2022 | 44.38353 | 1.07067% | 0.0114634% | 0.000616045 | 7.06199E-08 |
| 13/10/2022 | 44.86129 | -0.64102% | 0.0041091% | 0.000579082 | 2.3795E-08 |
| 12/10/2022 | 44.57464 | 0.96000% | 0.0092160% | 0.000544337 | 5.01661E-08 |
| 11/10/2022 | 45.00461 | 1.99691% | 0.0398764% | 0.000511677 | 2.04039E-07 |
| 10/10/2022 | 45.91235 | 0.51895% | 0.0026931% | 0.000480976 | 1.2953E-08 |
| 7/10/2022 | 46.15123 | -1.14525% | 0.0131160% | 0.000452118 | 5.92997E-08 |
| 6/10/2022 | 45.62569 | 1.04168% | 0.0108509% | 0.000424991 | 4.61155E-08 |
| 5/10/2022 | 46.10345 | 3.76252% | 0.1415652% | 0.000399491 | 5.65541E-07 |
| 4/10/2022 | 47.87115 | -2.62907% | 0.0691199% | 0.000375522 | 2.5956E-07 |
| 3/10/2022 | 46.62898 | -0.10251% | 0.0001051% | 0.000352991 | 3.7095E-10 |
| 30/9/2022 | 46.58121 | -0.92737% | 0.0086001% | 0.000331811 | 2.8536E-08 |
| 29/9/2022 | 46.15123 | 2.95789% | 0.0874914% | 0.000311902 | 2.72888E-07 |
| 28/9/2022 | 47.53672 | 1.09945% | 0.0120880% | 0.000293188 | 3.54406E-08 |
| 27/9/2022 | 48.06225 | 0.39683% | 0.0015748% | 0.000275597 | 4.33997E-09 |
| 26/9/2022 | 48.25335 | 1.57174% | 0.0247036% | 0.000259061 | 6.39975E-08 |
| 23/9/2022 | 49.01776 | -0.19512% | 0.0003807% | 0.000243518 | 9.27111E-10 |
| 22/9/2022 | 48.92221 | 0.67884% | 0.0046082% | 0.000228906 | 1.05485E-08 |
| 21/9/2022 | 49.25544 | -68.18477% | 46.4916265% | 0.000215172 | 0.000100037 |
| 20/9/2022 | 24.90758 | -3.74428% | 0.1401961% | 0.000202262 | 2.83563E-07 |
| 16/9/2022 | 23.99222 | 3.74428% | 0.1401961% | 0.000190126 | 2.66549E-07 |
| 15/9/2022 | 24.90758 | 2.86007% | 0.0817997% | 0.000178718 | 1.46191E-07 |
| 14/9/2022 | 25.63024 | 0.37524% | 0.0014081% | 0.000167995 | 2.36548E-09 |
| 13/9/2022 | 25.7266 | 2.95224% | 0.0871569% | 0.000157916 | 1.37634E-07 |
| 12/9/2022 | 26.49743 | -2.39201% | 0.0572172% | 0.000148441 | 8.49336E-08 |
| 9/9/2022 | 25.87113 | -0.56022% | 0.0031385% | 0.000139534 | 4.37929E-09 |
| 8/9/2022 | 25.7266 | -1.50947% | 0.0227851% | 0.000131162 | 2.98855E-08 |
| 7/9/2022 | 25.34118 | -1.14724% | 0.0131615% | 0.000123292 | 1.62272E-08 |
| 6/9/2022 | 25.05211 | 5.60895% | 0.3146027% | 0.000115895 | 3.64609E-07 |
| 5/9/2022 | 26.49743 | -1.83491% | 0.0336689% | 0.000108941 | 3.66793E-08 |
| 2/9/2022 | 26.01566 | -4.15939% | 0.1730055% | 0.000102405 | 1.77166E-07 |

##### Table 4.7 volatility calculation under EWMAs

The diagram above shows how the volatility is accounted for in a filtered historical simulation. The moving average of a time series of data can be calculated statistically by using exponentially weighted moving averages (EWMA), which gives more weight to more recent data points. With the most recent data point receiving the most weight, the method entails applying a smoothing factor to the historical data. The most recent data point's weight is set by the smoothing factor, which normally has a value between 0 and 1.

From the table above, the smoothing factor is set at 0.94 which is globally agreed to be the appropriate number which gives the most accurate prediction of tomorrow’s volatility. To find weight for the most recent price, we subtract 1 by the decay factor which is 0.94 this gives us 0.06 as the weight for the latest stock price. For the day before, we multiply 0.06 by 0.94 then we get the weight for 30 January 2023. To quantify the weighting factor for 29 January 2023 we multiply the weighting factor on the day 30 January 2023 by 0.94, thus, the weights keep falling exponentially till we reach a weight of 0 hence the name exponentially weighted moving averages.

The summation of the daily product of squared return and the weight will give us the daily variance which is then squared to get the volatility in equity prices as depicted by the table above.

Once the model residuals have been separated from the portfolio return series, normalize each residual by the corresponding conditional standard deviation. The unit variance, zero mean and I-id series are represented by these standardized residuals. For Bootstrapping, the I-id property is essential it facilitates the sampling procedure to safely avoid the trap of sampling from a population in which successive observations are serially dependent.

#### Figure 4.3 Adjusted returns

The results that were obtained from the Filtered historical simulation:



#### Figure 4.4 Filtered historical simulation results

The results obtained from Bootstrapping:



#### Figure 4.5 Bootstrapping results

The higher the negative Var the profitable the investment is thus; majority of investments are profitable at 99 percent confidence level after utilizing a mix of bootstrapping and filtered historical simulation to calculate the value at risk for various confidence levels.

## 4.4 Chapter Summary

Report the greatest gain and loss as well as the VaR over the 10- day risk horizon after simulating the portfolio’s returns at various confidence levels. Applying the Filtered historical simulation together with the bootstrapping, we assess market risk. When compared to the VaR estimations derived from the filtered historical simulation, it is anticipated that estimates indicate the probability of experiencing an extreme loss are greatly understated based on unadjusted volatility.

# CHAPTER V

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

## 5.0 Introduction

The main findings of the research, the analysis, and the inferences made from the research are summarized in this chapter. The chapter goes on to discuss the advantages of modeling market risk and the effects on companies of not assessing volatility.

## 5.1 Summary of findings

The techniques of Bootstrapping and Filtered historical simulation yield findings with value at risk. VaR employing daily equity returns is both statistically and economically viable. Value at risk was computed at four percentage intervals, one of which was adjusted for volatility and the other was not, ranging from 95 to 99 percent. In contrast to the numbers that were not modified for volatility, the one with the volatility adjustment gave us a strong negative value at risk, which denotes a larger profitability scale. This shows that the research was successful and that an investor might use the information to make strategic decisions when selecting their investment portfolio.

Filtered Bootstrap, however, easily passes the conditional coverage test whereas Historical Simulation does poorly on the independence test when comparing the two separate risk models. The explanation is that Historical Simulation is too sluggish, but Filtered Bootstrap can quickly modify VaR estimation. From 2000 to 2011 period, both models avoided exceeding the hit maximum ratio in several stock markets set by the regulatory framework. However, although Historical Simulation consistently exceeded the fixed boundary, Filtered Bootstrap consistently stayed inside the parameters in many markets.

Furthermore, while Historical Simulation is slower, Filtered Bootstrap is quicker in adapting the risk forecast to market volatility surges, and its worst value pie (failures frequency) is lower than the worst pie value in HS. Regulators accept 0 hits in 250 rolling windows, which can be a precautionary bias (models that estimate VaR poorly but in a very conservative manner are preferred to more conditional ones to account for large and unexpected losses), but this is not a desirable prescription for validating risk models. In fact, no hits imply that the model cannot pass coverage and independence tests; instead, a hybrid of these two produces better and more accurate results.

## 5.2 Conclusions

The methodology was based on the literature review of the previous scholars who undertook this study. Under parametric circumstances, forecasted losses tend to be high at 99% confidence level and the investments are also more profitable at that degree of confidence which corresponds to the investment norm that the higher the risk the lucrative the profit is. Using filtered historical simulation and the methodology just described, an assessment of market risk was carried out through the prediction of adjusted volatility and unadjusted. When comparing VaR estimates based on filtered historical simulation to estimates based on unadjusted volatility, it is assumed that the probability of experiencing an extreme loss is significantly understated.

## 5.3 Recommendations

While this article makes an attempt to predict market risk using sophisticated econometric methods, some questions remain unanswered. In a country with no economic stability, when quantifying market risk, it is of high significance to consider a number of factors. Below are some of the recommendations:

1. To improve such a study, one must select a specific time period where the economy and the currency of that economy are both stable in order to produce more satisfying results. Zimbabwe's currency situation and the country's economic stability must be examined. Given Zimbabwe's prior economic instability, it might be challenging to implement this there.
2. Take into account utilizing many models: To adequately account for the various facets of market risk, it is crucial to use multiple models. One model might not be enough to account for all the hazards to which the organization is exposed.
3. Combine historical and prospective data: Relying exclusively on historical data may not be sufficient in a nation lacking in economic stability. Forward-looking data must be included in the modeling process as well.
4. Regularly update the models: Market conditions in a country with no economic stability can change rapidly. It is important to regularly update the models to reflect the changing market conditions.
5. Include risk management strategies: A thorough risk management strategy includes more than just modeling market risk. To control the company's risk exposure, it's crucial to include risk management techniques like hedging, diversification, and insurance.

Overall, it is crucial to adopt a complete and dynamic strategy that includes numerous models, data sources, scenarios, stress testing, and risk management techniques when modeling market risk for a corporation functioning in an unstable economic environment.

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