

Volatility forecasting in small and mid-cap shares using EWMA and GARCH (1,1) models

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Dissertation accepted in fulfilment of the requirements for the degree *Master of Commerce in Risk Management* at the North-West University

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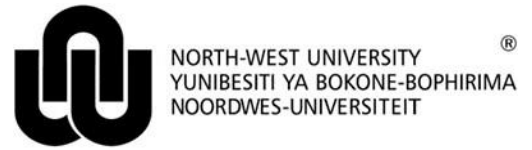
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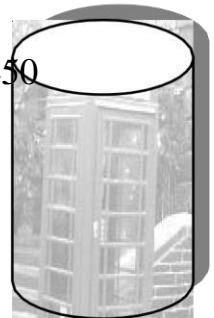
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REMARKS

The reader is reminded of the following:

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Each of the individual articles comply with the writing style requirements (i.e. the specific abstract, spelling, grammar, and referencing requirements) of the specific journal in which the applicable article has been published.

Articles 1 and 2 has been submitted for publication in Act Universitatis Danubius (EconomicaJournal). Chapter 4, article 1 and 2 have been accepted for publication in this journal. The editorial styles as well as the references for the rest of the dissertation, including articles, will follow the format prescribed by the North-West University Referencing Guide (2020).

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“Peace I leave with you; my peace I give you. I do not give to you as the world gives. Do not let your hearts be troubled and do not be afraid.”

John 14:27 NIV

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ABSTRACT

Considerable changes in share price returns are immediately followed by considerable changes of similar share price returns. Furthermore, inconsiderable changes in share price returns are immediately followed by inconsiderable changes of the same share price returns. The EWMA and GARCH (1, 1) models are used for volatility forecasting in small and mid-cap shares because of their shared trait in volatility clustering. The EWMA model is a derivative of the moving average family and the GARCH (1, 1) model is a derivative of the autoregressive conditional heteroscedasticity family. The weakness of the historical standard deviation is that the model assigns similar share price weights to all share price returns, whereas the EWMA and GARCH (1, 1) models inclusion to the study is to highlight the aforementioned weakness of the historical standard deviation. This is by using the EWMA and GARCH (1, 1) models to assign greater share price weight to recent share price returns and lesser share price weight to distant share price returns. Therefore, this study is aimed to investigate the preferable model to forecast volatility between the EWMA and GARCH (1, 1) models in small and mid-cap shares.

The EWMA and GARCH (1, 1) models were used for volatility forecasting for small and mid-cap shares as a result of the underwhelming performance of small and mid-cap shares that indicated a high risk investment. Rising government debt, the dissatisfying performance of GDP and an unreliable South African electricity public utility named Eskom were among factors that influenced the underperformance of small and mid-cap shares. Additionally, failure to preserve effective and ethical leadership with regards to successful corporate operations and governing outcomes over the last decade also had an influence on the performance of small and mid-cap companies. The COVID-19 pandemic outbreak, best described as an extreme global event also led to economic instability during 2020.

Based on the context of volatility forecasting within this study, volatility forecasting for small and mid-cap shares using the EWMA and GARCH (1, 1) models were conducted in order to support the empirical objectives. The results from the empirical objectives found that COVID-19 was an extreme event as it had a low probability of occurring, however, whenever it took place, it led to great damage to the global economy. Equally weighted share price returns that were evident using the historical standard deviation signified the use of the EWMA and GARCH (1, 1) models. The mid-cap optimal lambda was of a more considerable size than that of the small-cap shares. This was because of the considerable share price weighting since each weight was a constant multiplier of the prior day's weight.

According to the study's findings, it was preferable to make use of both models since they track a relative similar volatility of share price returns in small and mid-cap shares. Whenever there was an extreme event such as the COVID-19, the EWMA and GARCH (1, 1) models captured and recorded the event and changes in the optimal lambda were evident for small and mid-cap shares respectively. The outbreak of COVID-19 in South Africa proved to have been impactful as small and mid-cap companies endured a steep decline in share price returns. Share price returns were at their lowest in the period under analysis. Meanwhile, share price volatility was at its highest indicating the negative relationship between share price returns and share price volatility. The inverse relationship was evident from EWMA and GARCH (1, 1) as well as the historical standard deviation.

In order to achieve the primary objective, which is to forecast volatility in small and mid-cap shares using the EWMA and GARCH (1, 1) models, an event study methodology was used to examine a data sample of small and mid-cap shares between 1 January 2010 and 31 July 2020, using daily data. A descriptive comparison between the EWMA, GARCH (1, 1) and the historical standard deviation models was conducted with the inclusion of determining the optimal lambda. The use of the EWMA and GARCH (1, 1) models added to the importance of providing a holistic view of their advantages and disadvantages respectively. The advantages for the EWMA include the model's ability to continuously update its forecast in volatility, subject to new information availability, and reacting quicker not to the shock itself but in the role of recovering the marketplace while absorbing the shock. The disadvantage entails the failure to capture the asymmetry of volatility. Meanwhile, the advantage of the GARCH (1, 1) model is to readjust at a quick rate to the repercussions of the shocks in the financial markets, however, computational expensiveness disadvantages the model as only a select few, namely, investors, analysts, and traders could access its affordability.

The study recommends the use of other volatility forecasting models that would further elaborate on the weakness of the historical standard deviation and disclose findings that were not analysed under the EWMA and GARCH (1, 1) models. In addition, it is recommended to include the concept of mispricing of small and mid-cap shares amid the COVID-19 pandemic. The managerial implication would be to use the EWMA and GARCH (1, 1) models at the same time, as it was evident that both models tracked a relative movement of share price volatility.

Keywords: EWMA model, GARCH (1, 1) model, standard deviation, volatility forecasting, extreme event, COVID-19, and optimal lambda.

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LIST OF ABBREVIATIONS

ARCH : Autoregressive Conditional Heteroskedasticity

COVID-19 : Coronavirus disease 2019

EWMA : Exponentially Weighted Moving Average

GARCH : General Autoregressive Conditional Heteroskedasticity

GDP : Gross Domestic Product

HSD : Historical Standard Deviation

JSE : Johannesburg Stock Exchange

Rand : South African currency

SARB : South African Reserve Bank

SARS : Severe Acute Respiratory Syndrome

USA : United States of America

VaR : Value at Risk

WHO : World Health Organisation

CHAPTER 1: INTRODUCTION, PROBLEM STATEMENT AND STUDY OBJECTIVES

1.1 INTRODUCTION

For investors, volatility forecasting is a crucial fundamental element in managing the risk exposure of investment portfolios in the financial markets. It enables investors to make sound investment decisions (De Kloe & Amro, 2010). These decisions become the building blocks in the understanding of attractive returns when investing in the stock market. Rahahleh & Kao (2018) state that a thorough perception of volatility forecasting can be useful in areas that encompass risk management namely:- Value-at-Risk applications, option pricing, and portfolio diversification. As a result, after the financial crisis of 2007-2008, much attention has been directed towards ensuring that the financial markets, institutions and regulators are exposed to the current value of volatility of assets managed while, predicting their future values (Nilakantan & Mistry, 2013).

Nonetheless, a vast majority of investors are faced with the distinct challenge of forecasting the value of financial indicators and, thus those who had invested in the Johannesburg Stock Exchange (JSE) small and mid-cap companies during the 10-year period from 2010 to 2019 saw their investments decline from 12 percent to a negative 4 per cent (Van Vuuren, 2019). The significant decline or the underperformance of small and mid-caps was driven by the exposure that these companies encountered as they drew in the majority of their revenues from within South Africa. The period 2010 to 2019 experienced a 0.6 per cent real economic growth as financial positions became vulnerable in a low-growth environment (StatsSA, 2019).

The underperformance in small and mid-cap companies indicated the volatility in the stock market given the uncertainty surrounding financial models (Momentum, 2019). Uncertainty is commonly the foundation of financial models. On the other hand, volatility is regarded as accepting the realisation of that uncertainty (Marra, 2015). A simplified definition of volatility is that it measures the fluctuation of return around its mean or a dispersion in a probability density (Vasudevan & Vetrivel, 2016). Dispersion implies a range of possible returns for an investment. The general measure of dispersion is the standard deviation of a random variable, which in essence, is the square root of a variance (See-To & Yang, 2017). Standard deviation is one of the eight models that is used in forecasting volatility. It is also known to be the simplest model, taking into account historically, observed low volatility of assets returns in a short period of time (Ladokhin, 2009).

Marra (2015) points out other models in volatility forecasting such as the random walk, the historical mean, the moving average, the exponentially weighted moving average (EWMA), the

autoregressive moving average, the discrete historical, and the general autoregressive conditional heteroskedasticity (GARCH). For the purpose of the study, the EWMA and GARCH (1, 1) models will be used in forecasting volatility in small and mid-cap companies listed on the JSE using the small cap index (J202) and mid-cap index (J201). The EWMA and GARCH (1, 1) models were chosen because they capture long-term mean reversion of volatility, and capture near-term persistence and fluctuations in volatility (Marra, 2015). Between the EWMA and GARCH (1, 1), the model that outperforms the other either in small cap companies or mid-cap companies, will be used to provide thorough details on the manner in which investors can structure their investment portfolios so as to benefit from investing in the most appropriate asset class, specifically- equities (Huang & Oxman, 2015). Furthermore, the historical standard deviation will be used to highlight its weakness of assigning the same weight to all share price returns in the sampling period (Kritzman, 1991). This will highlight the importance of the EWMA and GARCH (1, 1) models.

Following the lost decade of the JSE, there was an outbreak of coronavirus, also commonly known as COVID-19 ('CO' stands for corona, 'VI' for virus, 'D' for disease, and '19' for the year 2019 when it occurred). On 11 March 2020, the World Health Organisation declared COVID-19 a global health crisis. The World Health Organisation (2020) describes the pandemic as a virus that is linked to a family of viruses that are similar to the Severe Acute Respiratory Syndrome (SARS). The SARS pandemic occurred in 2003 and it affected 26 countries, with more than 8000 cases and at least 774 casualties being reported (Wilder-Smith, *et al*, 2020). Both viruses are extreme events which typically have a low probability of occurring but whenever they do, they leave behind traces of a destabilised economy. About 40 billion dollars was attributed towards the SARS outbreak, while a trillion dollars is expected to be attributed towards COVID-19 (World Economic Forum, 2020). The period under analysis is extended to 31 July 2020 to accommodate the high levels of volatility and small- and mid-cap share price returns as a result of the COVID-19 pandemic. This significantly contributes to the determination of the optimal lambda, as a result of the aforementioned extreme event.

1.2 PROBLEM STATEMENT

Standard deviation is regarded as the most preferred measurement of volatility as it is useful in forecasting the implied and historical volatility of individual equity securities (Samsudin & Mohamad, 2016). However, Marra (2015) argues that, based on the standard deviation, consistent and persistent over-estimation of volatility, small cap and mid-cap companies share investments declined from 12 per cent to a negative 4 per cent. Weak portfolio management models, which had factored in the standard deviation as a measure of volatility, contributed towards the significant

decline from 2010 to 2019 (Van Vuuren, 2019). As a result, 2010 to 2019 was named the lost decade of the JSE for small and mid-cap shares. The EWMA and GARCH (1, 1) models are useful for investors to forecast the volatility in the share prices of small and mid-cap companies. Hence, as an approach to estimating volatility, EWMA will be used to overcome the key weakness of the historical standard deviation, since the latter assigns the same weight to all the returns in the historical window (Hol, 2003). Taking it a step further, generalising the EWMA using the GARCH (1, 1) model assigns exponentially declining weights (Guermat & Harris, 2002). This analysis will also be valuable to investors who are actively holding shares in listed small and mid-cap companies, as well as to potential investors who seek to hold shares in such companies (Le Roux, 2018). Meanwhile, with the period under analysis extended to 31 July 2020, amid the outbreak of the COVID-19 pandemic, the optimal lambda will be examined.

1.3 RESEARCH QUESTIONS

- Between the EWMA and GARCH (1, 1), which model is better than the other for forecasting volatility in small and mid-cap shares?
- How will investors benefit from holding shares based on the EWMA and GARCH (1, 1) models outcome?
- How can investors perceive share volatility in small and mid-cap companies?
- Why was the period 2010 to 2019 named the lost decade of JSE small and mid-cap shares?
- What happened to small and mid-cap share price returns between 31 December 2019 and 31 July 2020?
- Which category of shares between the small and mid-cap shares was the hardest hit?
- What was the impact of COVID-19 on the optimal lambda on 31 July 2020?

1.4 OBJECTIVES OF THE STUDY

1.4.1. Primary objective

The primary objective of this study is to forecast volatility in small and mid-cap shares using the EWMA and GARCH (1, 1) models.

1.4.2 Theoretical objectives

In order to achieve the primary objective, the following secondary objectives were formulated for the study:

- Contextualise the significance of volatility forecasting of asset returns in small and mid-cap shares to investors' share portfolio construction;
- Consider the benefits and drawbacks from holding shares based on the EWMA and GARCH (1, 1) models;
- Identify the event that caused extreme volatility during this period; and
- Investigate the factors that led to the underperformance of small and mid-cap shares.

1.4.3 Empirical objectives

Empirical objectives for EWMA and GARCH (1, 1) models on small-cap shares using the small-cap share index (J202).

In accordance with the primary objective and theoretical objectives of the study, the following empirical objectives were formulated:

- Analyse the EWMA and GARCH (1, 1) models in forecasting volatility in small cap shares using the small cap index (J202);
- Investigate the relationship between EWMA and GARCH (1, 1) for small-cap shares using daily data;
- Assess the closing share prices, relative share prices, daily returns, squared returns, and the impact of the constant ratio of consecutive weights in accordance with the EWMA and GARCH (1, 1) models; and
- Determine the optimal lambda post the lost decade of the JSE, including the period under which COVID-19 is active.

Empirical objectives for EWMA and GARCH (1, 1) models on mid-cap shares using the mid-cap share index (J201).

- Examine the EWMA model and the GARCH (1, 1) in forecasting volatility in mid-cap shares using the mid-cap index (J201);
- Investigate the relationship between the EWMA and GARCH (1, 1) models for mid-cap shares using daily data;
- Analyse the closing share prices, relative share prices, daily returns, squared returns, and the impact of the constant ratio of consecutive weights following the EWMA and GARCH model; and
- Determine the optimal lambda post the lost decade of the JSE including the period under which COVID-19 is active.

1.5 METHODOLOGY

1.5.1 Data and data availability

The study focused on the small cap index (J202) and mid-cap index (J201) for the period 1 January 2010 to 31 December 2019, in particular, forecasting volatility using historical data during that specified period. This highlighted the most appropriate model to be used in small-cap shares and mid-cap shares respectively and included the benefits towards the investors' investment portfolio construction specifically, equities. Additionally, the Historical Standard Deviation (HSD) was also used to highlight its weakness of assigning the same weight to all share price returns in the sampling period. The period was extended to 31 July 2020 for the inclusion of the extreme event brought about by the outbreak of COVID-19 global pandemic and its impact on the optimal lambda.

Data were collected from a reputable source namely: IRESS INET BFA to forecast volatility for small and mid-cap shares. The EWMA and GARCH (1, 1) models on small, and mid-cap shares using the small-cap share index (J202) and mid-cap share index (J201) were used for small cap shares and mid-cap shares respectively, for the above mentioned specified period. Two articles titled, volatility forecasting during extreme market events using the small-cap share index and volatility forecasting during extreme market events using the mid-cap share index were thoroughly discussed in chapter 3 and chapter 4 respectively, to elaborate on the use of the share index J201 and J202.

1.5.2 Model specification

The EWMA model is a particular phenomenon, whereby the weights decline sharply when basically moving back in time to the previous share price. The process of assigning weights to each share price leads to a formula for forecasting volatility. As a result, the equation for EWMA is as follows:

$$\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1 - \lambda)u_{n-1}^2$$

Volatility as defined by σ_n will be a variable for day n which is made at the end of day n-1. It is calculated from σ_{n-1} being the forecast made at the end of day n-2 of volatility for day n-1. Meanwhile, u_{n-1} being the current daily percentage in the variable. EWMA is regarded as a favourable model since it is made to keep track of changes in volatility.

The difference between the GARCH (1, 1) and EWMA models is the long-run variance assigning γ as its weight. Hence, σ_n^2 is calculated from the long-run variance rate depicted as V_L . The equation for GARCH (1, 1) is as follows:

$$\sigma_n^2 = \gamma V_L + \alpha \sigma_{n-1}^2 + \beta \sigma_{n-1}^2$$

Whereby α is the weight assigned to σ_{n-1}^2 . β is the weight assigned to σ_{n-1}^2 . As the weights must sum up to 1, the depiction takes the following form, as $\gamma + \alpha + \beta = 1$

1.5.3 Statistical analysis

Statistical analysis for volatility forecasting during extreme market events using the small-cap share index.

Data for the JSE small cap shares was used to apply the EWMA and GARCH (1, 1) models. Small-cap share prices of the JSE for the past 10 years, commencing from 1 January 2010 to 31 December 2019, were taken into account. The period 1 January 2020 to 31 July 2020 was also taken into consideration for the analysis of the optimal lambda due to COVID-19. To apply the models, a parameter $\lambda = 0.931$ was used as an estimator, as determined on the end of the period under analysis. However, this parameter was rarely constant and continuously changed based on the impact of the financial crisis, and pandemics. Bollen (2015) indicated that lambda was a smoothing parameter and should always be less than 1. It varied between 0 and 1 (Rigby & Stasinopoulos, 2014). Moreover, the analysis considered the extreme values that COVID-19 introduced, so the focus was on tail regions of the empirical distribution for small-cap shares.

Statistical analysis for volatility forecasting during extreme market events using the mid-cap share index.

The mid-cap share index (J201) was suitable for the long-term investor who anticipated a higher return over time. As a result, the JSE from 1 January 2010 to 31 December 2019 was statistically analysed with respect to the closing share prices and daily returns using the EWMA and GARCH (1, 1) models. Similar to small-caps, the period 1 January 2020 to 31 July 2020 was taken into account whilst applying a parameter $\lambda = 0.974$.

1.6 Ethical considerations

The study adheres to the principles of quality and integrity, however, its independence is exposed to minimal risk, since it will be making use of secondary data.

1.7 Contribution of the study

The study contributes to the literature in various ways. Firstly, the volatility forecasting on the underperformance of small and mid-cap shares in the 2010 to 2019 decade, is highlighted using the EWMA and GARCH (1, 1) models. This will be relevant to active investors and potential investors in identifying which of the two models forecasts volatility better. Secondly, investors will fully comprehend the analyses of these models on the shares they hold in listed companies. This will enable the investors, who have an objective of realising positive asset returns to have more knowledge towards the allocation of their investments in shares based on the volatility of daily share prices. Finally, the major contribution is its analysis of the involvement of the extreme event namely: the COVID-19 pandemic and the impact on the optimal lambda.

1.8 Chapter classification

This study will be conducted in article format, the publishable articles have been split into the following chapters in the final submission, preceded by chapter 1 an introduction (including a research methodology section) and summarised by means of a conclusion; and chapter 2 literature review. The rest of the study unit is structured as follows:

Chapter 1: Introduction and objectives

This chapter introduces the topic of the study and explains the overall research objectives as well as the theoretical and empirical objectives and the research methodology used in the study.

Chapter 2: Literature review

The literature review provides the background and context of the research problem. It would be helpful to comprehend the significance of small and mid-cap companies within the economy of South Africa and the EWMA and GARCH (1, 1) models for estimating volatility.

Chapter 3: Volatility forecasting during extreme market events using the small-cap share index

The chapter focuses on the importance of the EWMA and GARCH (1, 1) models in the small cap share index (J202). Chapter 3 also seeks to establish which one of the two models would be better, based on the slight accuracy of volatility forecasting. The significance of the performance of small cap shares will be contextualised within this chapter. Along volatility forecasting, the optimal lambda will be analysed with regard to its change before and during the outbreak of COVID-19. Lastly, the chapter will also attempt to determine the extreme values that the pandemic introduced.

Chapter 4: Analysing volatility forecasting extreme market events using the mid-cap share index

Chapter 4 identifies and elaborates on the more preferred model between EWMA and GARCH (1, 1) in the mid-cap share index (J201). The performance of mid-cap shares will be analysed in context within this chapter. The chapter also makes an analysis of the optimal lambda during the lost decade of the JSE and of the COVID-19 pandemic periods.

Chapter 5: Overall findings, conclusion and recommendation

In Chapter 5, the results and findings of the study will be presented to forecast volatility in the sample of small and mid-cap share prices as at 31 July 2020. A consensus will be reached and it will be supported by theory and data. Relevant recommendations regarding the forecast of volatility will be made, as advised by Errais & Bahri's (2016) study, which states that standard deviation is considered to be a good measure of a stock's volatility. However, the EWMA and GARCH (1, 1) models take multiple factors into account since they are useful in a long period, rather than in a short span of time, as the standard deviation estimates (Ding & Meade, 2010).

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CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

The key objective of this study is to contextualise the significance of volatility forecasting of the small and mid-cap share price returns to investors' share portfolio construction. Forecasting will be constructed with the use of the EWMA and GARCH (1, 1) models. The study further intends to provide thorough understanding of the concepts of the EWMA and GARCH (1, 1) models from the perspective of forecasting volatility. The benefits and drawbacks of the EWMA and GARCH (1, 1) models are brought into account, which is important towards the selection of the most preferable model for forecasting volatility in small and mid-cap shares. To achieve this, it is important to understand the key features which make the EWMA and GARCH (1, 1) models preferable tools for forecasting volatility. In addition, the factors that led to the underperformance of small and mid-cap shares will be taken into consideration. This chapter further places emphasis on the concept of volatility forecasting, the type of volatility in shares between the historical and implied, and the events that led to extreme volatility and staggering share price returns on the JSE. It is also important to discuss the standard deviation, since it is the standard metric for measuring risk, and is applied to the JSE returns. Furthermore, the standard deviation is commonly used as a model in volatility forecasting. Lastly, the importance of small and mid-cap companies within the South African economy is taken into consideration.

2.2 VOLATILITY FORECASTING IN THE STOCK MARKET

The global financial crisis of 2007/08 highlighted the importance of volatility forecasting in the stock market (Knight & Satchell, 2007). Firms experienced a shortage of cash flows and earnings to fund their projected investments (Minton *et al.*, 2002). The market capitalisation of the world's top 15 banks declined from 1.7 trillion dollars in the second quarter of 2007 to 500 billion dollars by 20 January 2009 (Baxter, 2009). This signified extreme volatility in share price returns in which the attention of the concept of volatility was essential.

Volatility is associated with uncertainty and a measure of risk in financial markets, in which the investors who are fixed on risk-adjusted returns observe the fluctuations in stock prices over time and as such make use of volatility targeting (Anderson *et al.*, 2005). According to Perchet *et al.*, (2015), volatility targeting is a systematic strategy that is deployed to rebalance a risky asset and cash. This enables the ability to target a constant level of risk in a specified period (Hocquard *et al.*, 2010). Nonetheless, the challenge in forecasting volatility in the stock market is based on the ineffectiveness in hedging against changes in volatility and thus exposing the investment portfolio

to tail risk which deteriorates a portfolio's risk-adjusted returns (Hocquard *et al.*, 2015). The bankruptcy of Lehman Brothers in September 2008 is an example of tail risk. By definition, tail risk is an event with a small probability of taking place but when it occurs, it leads to severe losses that send shock waves through financial markets (Constable, 2015). The example of the Lehman Brothers is among the many tail risks encountered in the stock market, whereby the investors who had invested in that global financial service firm found themselves on the far left tail of the distribution of returns (Hafner, 2015). Egan (2018) points out that the continuous subprime mortgage crisis led the Lehman Brothers to bankruptcy, declaring 639 billion dollars in assets and 613 billion dollars in debts. This made it the largest filed bankruptcy in the United States of America. As the concepts of volatility targeting and tail risk are of importance towards rebalancing risky assets and events that cause shock waves in the stock market respectively, the following section emphasises the properties of volatility and the types of volatility forecasting.

2.2.1 Properties of volatility

In any structure of every financial model, there is an effect of uncertainty that is based on the behaviour of investors, which spills over to stock prices (Marra, 2015). Overtime, volatility reverts to the mean, and as new information is revealed to investors, there is an engagement in the form of carrying out different views on share prices in order to realise the negative relationship between volatility and return (Kuhe & Audu, 2016). The properties of volatility namely: volatility clustering, leverage effect, and mean reversion, are discussed in detail below.

2.2.1.1 Volatility clustering

Marra (2015) explains that, over time, the occurrence of volatility clustering is based on the analogy that sizeable changes in financial returns are instantaneously followed by sizeable changes of the same returns and small changes of the same returns instantaneously follow small changes in financial returns. This demonstrates a phenomenon that can be well explained with a switch between high and low volatility which adds towards the clustering of volatility (Cont, 2005). Also, volatility clustering is driven by investor inertia rather than the switching mechanism, as it does not provide a more thorough understanding of the term. Investor inertia occurs mostly during periods of market uncertainty (Shin *et al.*, 2019). Torr (2020) points out that few investors are willing to trade in these markets, since those who decide not to take part are driven by the fear of loss or fear of the unknown (lack of new information). Fear of change also plays a role, which subsequently leads to investors forgoing lost opportunities (Mishra, 2019). Figures 2.1 and 2.2 illustrate volatility clustering for small and mid-cap shares respectively.

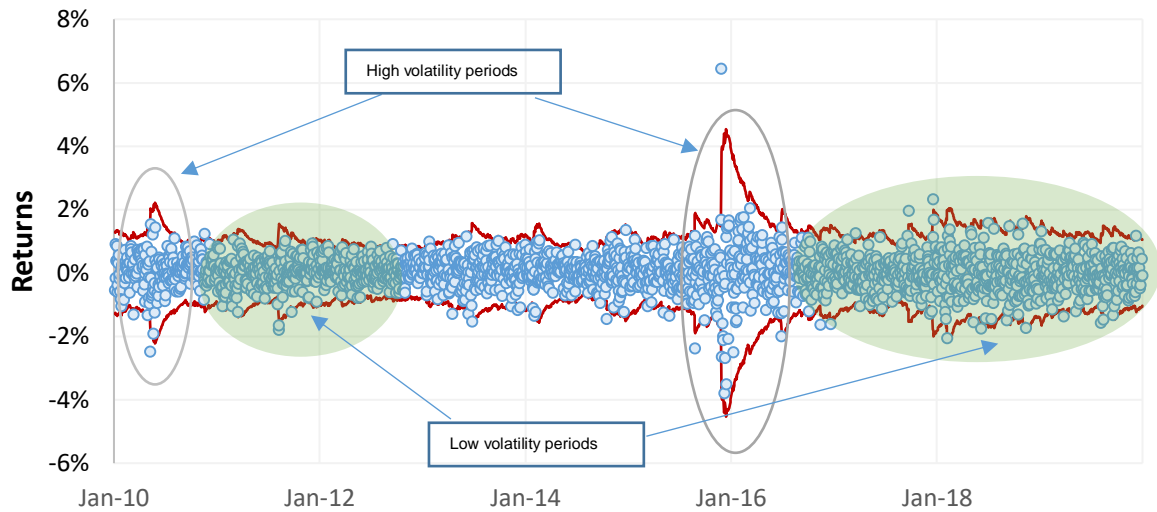


Figure 2.1: Volatility clustering for small-cap shares

Figure 2.1 indicates volatility clustering, which is depicted in the red lines. The levels of these red lines range from low to high volatility. During periods of low volatility, small changes are subsequently followed by small changes (Moffatt, 2019). This phenomenon was observed as there was an extended period of low changes from July 2010 to November 2015. However, the price return of small-cap shares was followed by a period of high volatility from December 2015 to January 2016.

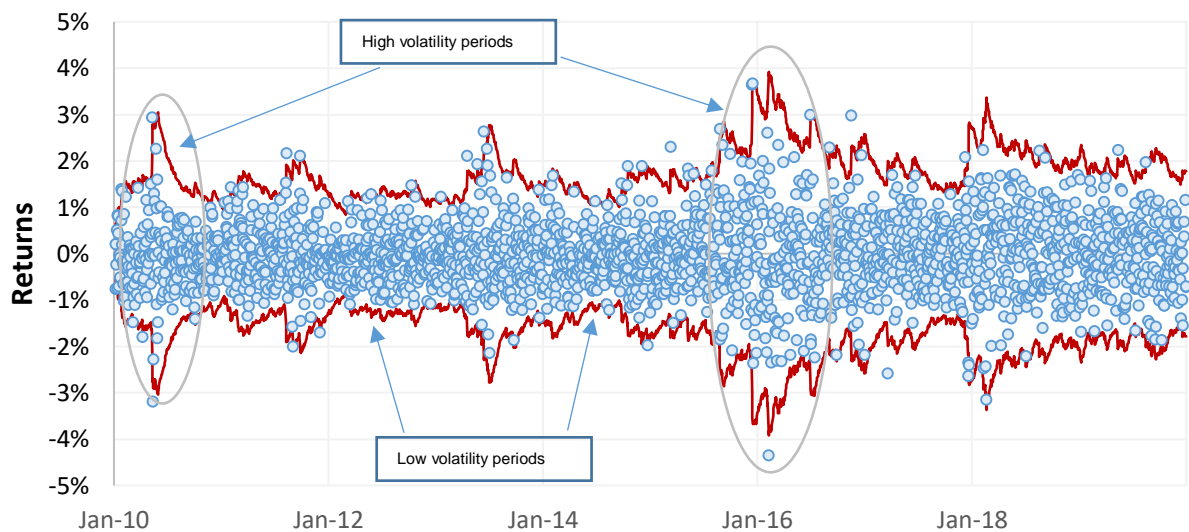


Figure 2.2: Volatility clustering for mid-cap shares

Figure 2.2 indicates volatility clustering, as shown in the red lines. A high volatility period was recorded during the market uncertainty that was caused by political turmoil in 2016 and 2017 (Hogg, 2016). Another high volatility period was also recorded in the year 2018. In both the instances in which high volatility was captured, moderately large changes in volatility were

followed by similar changes in volatility whereby mid-cap share price returns were clustered in a range of one and negative one per cent. This phenomenon signifies the negative relationship between volatility and share price return. The other property of volatility namely: the leverage effect, is discussed in the sub-section below.

2.2.1.2 Leverage effect

Share prices decline significantly because of various reasons. Firstly, the prices fall due to factors that relate to the company itself, such as accounting irregularities, and insider trading, among others, which are commonly referred to as fraud risk. This was well documented within the Steinhoff saga – dubbed as the biggest case of corporate fraud in South African business history, as its share price declined from 46 rand and 6 rand in three days (Fin24, 2017). Secondly, ENCA (2020) draws attention to the outbreak of COVID-19, which has caused panic in the stock exchange as the JSE was down 12 per cent surpassing the 11.7 per cent recorded on 20 October 1987 (known as Black Monday). Finally, behavioural finance namely, factors such as investor emotions, perceptions, and confidence play a huge role in the decline in share prices (Thompson, 2017). Amid the rise of the dotcom bubble in 1995, the internet market began to gain traction and the majority of people without prior knowledge of trading bought shares based on expected higher future returns and this resulted in a burst (Joosten, 2012). These factors leading to a decline in share prices fostered companies to be more leveraged since their value of debt increased the value of their respective equity and, consequently, the share price became highly volatile (Marra, 2015). Mean reversion is the final property of volatility.

2.2.1.3 Mean reversion

The other property of volatility in share prices is based on the fact that it reverts to the mean over time (Goudarzi, 2013). Kuhe & Audu (2016) claim that financial assets display an underlying volatility level, whereby in periods of high or low volatility, the assets tend to fall back as they gradually return to their average level. Yet, Yee (2005) also discusses the notion that efficient markets may display mean reversion in instances where share prices are based on the information that is made available. Likewise, a share price is determined by the expected return per share, and as such, mean reversion is perceived when the expected returns are mean-reverting (Kuhe & Audu, 2016). Option-implied volatility and historical time-series volatility are the focus types of volatility forecasting.

2.2.2 Types of volatility forecasting

There are various types of volatility for forecasting concerning share returns, such as the historical time series and option-implied volatility, as represented in Figure 2.1. Moreover, the following sections provide a detailed explanation of these types of volatility.

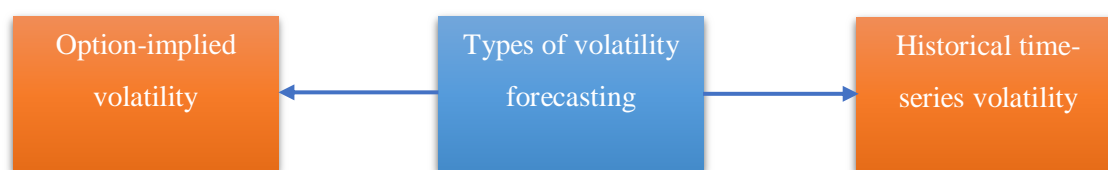


Figure 2.3: Illustration of types of volatility forecasting

2.2.2.1 Option-implied volatility

The first type of volatility forecast that will be discussed is option-implied volatility, which is often used by traders to indicate the probability of market volatility (Samsudin *et al.*, 2016). Option-implied volatility is a derivate of the price of an option, thus, indicating what the market implies regarding the share volatility when forecasting (Caporale & Teterkina, 2019). Option-implied volatility also used to forecast the future average volatility of the remainder of the life of the underlying asset of the option contract (Hull & White, 1987). From the perspective of traders, option-implied volatility seems more inclined than the historical time-series volatility because it factors in all market expectations (Fxoptions, 2020). Wolfinger (2019) discusses that the occurrence of an event, such as a company announcing its earnings, the implied volatility of options reaches expiration in the same month that it is affected. This can be done by computing an expected range calculation, such as the high and low of the share price by expiration. In turn, this enables the traders to have an opportunity to see whether the market is in agreement with their outlook, which is of help towards measuring risk and return. The historical time-series volatility which is the main focus of this study, is discussed in the sub-section below.

2.2.2.2 Historical time-series volatility

The historical time-series volatility forecast is expressed mathematically, based on the variation of past stock prices that are either tracked daily, weekly, monthly or yearly (Parasuraman & Ramudu, 2011). Dey (2019) elaborates that it is also used as realised volatility, since it is based on realised share prices, while also indicating the amount of change that occurred in the past. It is based on historical observation, without reflecting expectations of future price volatility. It makes provision for indicating the amount the share price could move in the future, based on past trends, instead of

predicting future trends (Ederington & Guan, 2006). According to Samsudin *et al* (2016), low historical volatility could be an indication that the stock price has been fluctuating at a low rate over a while. As the properties of volatility and types of volatility forecasting discussed, the inclusion of the standard deviation is also of utmost importance to the study because it contributes to the concept of risk and share price volatility.

2.3 STANDARD DEVIATION

Standard deviation in the field of risk management measures the risk of asset returns, as investment decisions are based on two main investment elements namely: risk and return (Errais & Bahri, 2016). As volatility measures the fluctuation of a share price, the standard deviation is its primary measure that is used by traders and analysts (Kritzman, 1991). It is the preferred model for forecasting volatility after the stock market crash of 2008 whereby the Dow Jones industrial average dropped 777.68 points in intraday trading (Rauchway, 2019). Errais & Bahri (2016) explain that the stock market crash enabled a focus on regulation to manage price volatility. Anshuman (2003) highlights regulatory measures to manage price volatility. Regulatory measures are as follows: price limits – applying a cap on daily price changes to reduce default risk; transaction taxes – aimed at controlling fierce speculators in the financial markets; margins – primarily used to limit systemic risk in the economy; and circuit breakers – to control volatility by mitigating system failure as a result of operational backlogs.

Standard deviation is regarded as the preferred model in volatility forecasting based on its simplicity, it is less expensive to conduct and remains as a benchmark for analysis against which alternative models can be used. However, like any other model, it has a major drawback. It assigns the same weight to all share price returns in the sampling period (Milton, 2019). The assigning of the same weight is key to the introduction of the EWMA and GARCH (1, 1) models, which build on rectifying the drawback and can be of aid in forecasting volatility in small and mid-cap shares (Nilakantan & Mistry, 2013). The significance of the period 2010 to 2019 for small and mid-cap shares is explained below.

2.4 MEASURES OF VOLATILITY FORECASTING

2.4.1 Exponentially Weighted Moving Average

The EWMA is a derivative of a family of the moving averages, which are used as technical lagging indicators (Kolkova, 2018). Fayek, *et al* (2013) states that the analysis of lagging indicators depends on past events in the market, rather than the leading indicators based on the prediction capabilities on future market direction. Their function is to showcase how a share price has moved,

on average, over a certain period (Milton, 2019). Moving averages are key to trend analysis – highlight trends, detect trend reversals and make provision for trade signals. Simple moving average, exponential moving average, and weighted moving average are the bedrock of the moving average family. From a technical analysis perspective, the simple moving average tracks the average of the closing share price over a specific number of periods (Kristopher, 2014). It is subject to the share price. Hence, when a share price fluctuates, the moving average does the same. Nevertheless, the same weight assigned to all share prices is the limitation towards the simple moving average and, as a result, the weighted moving average and exponential moving average were modelled to highlight this.

The focal point of the weighted moving average is based on the premise that more weight on the latest data is more analysed while weighting on past data is less focused on (Perry, 2010). Similarly, the weighted moving average puts more emphasis on the latest, rather than on the past share prices. This serves as a shared characteristic with the exponential moving average. Fidelity (2020) also points out that the weighted moving average helps to analyse the trend direction of a share price (whether to buy or sell, based on the drop in price below the weighted moving average or movement beyond the weighted moving average). Raudys & Pabarskaite (2016) explain that since all moving averages produce a single smooth line that can be of assistance in the illustration of the share price movement, both the exponentially weighted moving average and exponential moving average are used interchangeably. As such, more weight is provided for the latest data.

Besides the variation of weights to all share price returns under analysis, the introduction of EWMA towards volatility offers the following advantages. The model continuously updates its forecasts in volatility, subject to new information availability. It reacts quicker, not due to the shock itself, but in the role of recovering the marketplace while absorbing the shock. Its complexity provides the model with an edge to conduct thousands of financial calculations on share price returns and volatility (Reynolds & Stoumbos, 2006). However, the model is not immune to drawbacks. Marra (2015) argues that the model fails to capture the asymmetry of volatility and, most importantly, it recovers more slowly from large shocks, whereas the GARCH (1, 1) model is more dominant on the quickness of recovering from large shocks in the marketplace. Nonetheless, the use of the EWMA model for analysis by investors, analysts, and traders provides a more thorough and less expensive approach towards volatility forecasting than using the historical standard deviation.

2.4.2 General Autoregressive Conditional Heteroskedasticity

The GARCH model is a derivative of the autoregressive conditional heteroskedasticity (ARCH) family. The key aspects of the ARCH models are autoregressive, which implies that the next day's volatility is a regressed function of today's volatility. The term conditional means that next day's volatility is subject to the condition of the most recent volatility, whereas heteroskedasticity implies that volatility is non-constant, as it fluctuates over time (Engle, 1982). Parihala (2010) outlines that GARCH reverts on lagged terms, since these terms are depicted as variance (volatility) or squared returns. In general, the GARCH (p, q) model reverts on (p) squared returns and (q) variances. As a result, GARCH (1, 1) is stated as one lag on previous squared return and one lag on previous variance (Williams, 2011).

The GARCH (1, 1) model for volatility estimation and forecasting analysis takes into account the assumption that the present day's volatility is dependent on a constant; the previous day's news on volatility (fundamental analysis) and the previous forecast variance (Szylar, 2010). Because of its sophistication, the model is capable of handling volatility clustering well. As described earlier, volatility clustering is whereby large volatility movements are followed by large volatility movements. Similarly, small movements follow the same analogy. Li *et al* (2006) state that more weight is prioritised to the latest observations of share prices, which is a shared characteristic with the EWMA model. Despite the shared characteristic, the GARCH (1, 1) model is well-known for its quick rate of readjusting to the repercussions of shocks in the financial markets – making it more sophisticated and more expensive than EWMA, however, this does not rule out the EWMA model for analysis as already stated that it reacts quicker, not due to the shock itself, but in the role of recovering the marketplace while absorbing the shock (Baybogan, 2013). The computational expensiveness of GARCH disadvantages the model, it is infrequently used by investors, analysts, and traders.

Lalwani *et al* (2019) also argue that since the GARCH model is a family of the ARCH models, it breeds the same weakness. Such a weakness is based on the assumption that, regardless of the shock being negative or positive, it has the same effect on volatility, but in general, share prices have a varying response to both negative and positive shocks, depending on the magnitude of the shock itself (Bass, 2017). Despite the research mentioned above, it is evident that standard deviation is factored in from option-implied volatility, historical time-series volatility, the moving averages, and ARCH models, thereby forming the basis of volatility forecasting. However, it is of importance to deduce which model is best used as an alternative in small and mid-cap shares for investors traded in the JSE.

2.5 THE LOST DECADE OF SMALL AND MID-CAP SHARES

The JSE small and mid-cap companies experienced a consequential decline in share prices from 14 per cent on November 1st 2010 to negative 4 per cent on March 1st 2019 (Van Vuuren, 2019). This was largely driven by factors affecting share price volatility, which influenced investors' investment decisions (Sainy, 2016). Macroeconomic factors such as GDP, inflation, interest rate, and government debt level contributed towards the decline. Pitro (2019) also states that failure to comply with corporate governance by specific JSE-listed companies contributed to the decline in the overall plunge in share prices undergone in small and mid-cap shares. The lost decade of JSE for small and mid-cap shares from 2010 until 2019, which is the period used for this study analysis, extending the period to 31 July 2020 for further analysis of the extreme value theory concerning the impact of the outbreak of COVID-19 on share prices.

The lowest share price experienced before the period under analysis was at two per cent during the 2008 financial crisis (Van Vuuren, 2019). However, as of 1 March 2019, the lowest share price, at negative four per cent, was triggered based on real GDP, which in the first quarter of 2019 stood at negative 3.2 per cent (StatsSA, 2019). Furthermore, the inflation rate was at 0.83 per cent at the beginning of February 2019, then it dropped by 0.01 per cent to stand at 0.82 per cent at the beginning of March 2019, and subsequently, it declined to 0.54 per cent by the end of March 2019 (Inflation. EU, 2019). Other factors as the interest rate were also factored in. Nonetheless, the prime lending rate remained at 10.25 per cent for the first month of 2019 (SARB, 2019). The actual causes behind the lost decade of JSE for small and mid-cap shares are outlined in-depth in Figures 2.5.1.1; 2.5.1.2; and 2.5.1.3. Figure 2.4 illustrates South Africa's real GDP performance for every quarter from 2010 to 2019, also indicating that in the past five years (2014 to 2019). There has been negative growth. The following sub-sections discuss the three macroeconomic factors namely, real GDP, inflation rate, and prime lending rate contributing to the decline of share price returns together with the investors' confidence.

2.5.1.1 Real GDP

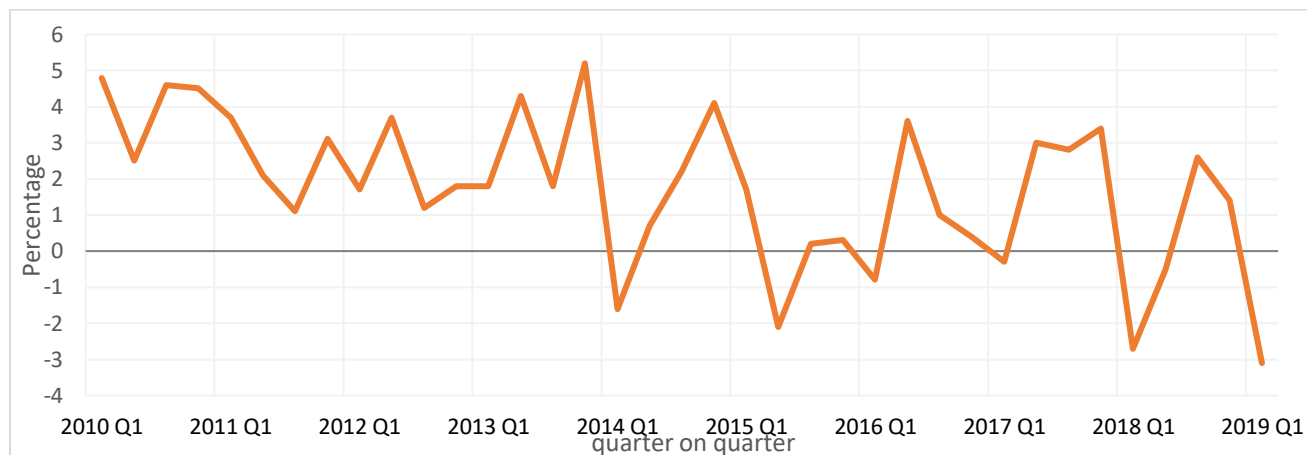


Figure 2.4: South Africa's Real GDP for quarter-on-quarter (2010-2019)

Sources: SARB (2019)

According to Amadeo (2020), real GDP is a measurement of economic output which takes into account the impact of inflation or deflation. It is a necessary macroeconomic indicator as it makes provision on a broader view of growth in comparison to nominal GDP (Callen, 2020). In the absence of real GDP, a country will be of the view that it is increasing in production of goods and services produced in a single year within its boundaries, meanwhile, it is only the prices that are going up (Dyran & Sheiner, 2018). Real GDP is crucial for investors that buy and hold their investments, nevertheless, real GDP is a lagging indicator since it indicates past fluctuations in the economy and later revised to the public whereas investing is more of a forward-looking process (Pot *et al.*, 2018). Kennon (2019) adds that buying and selling shares is fundamentally based on the investors' assumption for the direction of GDP growth in the future, and the impact on their investments, instead of past performance.

Real GDP in the fourth quarter of 2013 was at 3.8 per cent and was later revised to 5.2 per cent due to an increase in the economic activity of the manufacturing industry, and the mining and quarrying industry. These industries contributed 1.8 percentage points, based on 12.3 per cent and 0.8 percentage points, based on 15.7 per cent respectively (StatsSA, 2014). Such an increase is good for the South African economy, however, the majority of small and mid-cap companies listed on the JSE are included in the wholesale, retail, motor trade, catering, accommodation, finance, real estate, and business services. They each contributed 0.3 percentage points on 1.5 per cent, respectively (StatsSA, 2014).

The majority of small and mid-cap companies are South African based and they forfeit on the benefits of dual listing. Investors are unable to take advantage of undervalued share prices in one

market, which helps towards the flow of capital to the other market and being in a position of profiting, based on price differences between the two markets (Hauser *et al.*, 2011). As a result, negative growth in real GDP at negative 1.6; 2.1; 0.8; 0.3; 2.7; and 3.1 for 2014 Q1; 2015 Q2; 2016 Q1; 2017 Q1; 2018 Q1; and 2019 Q1, respectively. This was subject to a decline in critical sectors such as agriculture, mining, and manufacturing industries by 0.3; 0.8; and 1.1 per cent, respectively, as of 2019 first quarter (StatsSA, 2019). These sectors employ the most workers. Meanwhile, the unemployment rate remained at 29.1 per cent as of the first quarter of 2019 (South African Market Insights, 2020). The second macroeconomic factor is the inflation rate.

2.5.1.2 Inflation rate

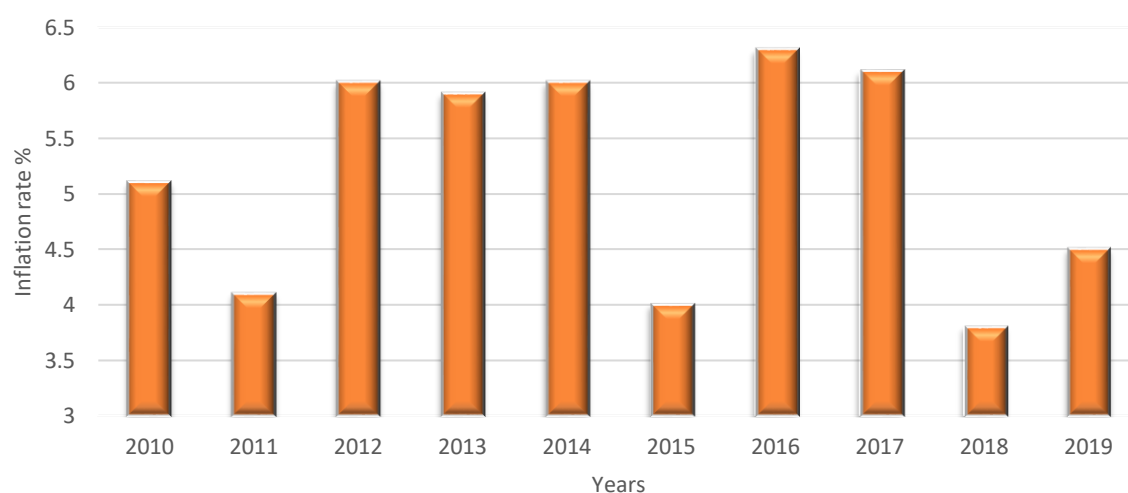


Figure 2.5: Annual inflation rate (2010-2019)

Source: SARB (2019)

The annual inflation rate is the change in the consumer price index for every item of the relevant month (i.e. the month of March for each year) of the current year in comparison to the consumer price index for each item of the same month in the previous year, expressed as a percentage (StatsSA, 2010). Inflation is viewed as a threat to investors, since it weakens real savings and investment returns (Pimco, 2016). As a result, for investments to yield a good return, they should keep up with the rate of inflation, so that there is an increase in real purchasing power (Usbank, 2019). The annual inflation rate for 2016, at 6.3 per cent, was the highest and investors in small and mid-cap companies with less diversified portfolios encountered their value of the principal on fixed income securities being undermined (Pimco, 2016).

Hence, the majority of investors invest in the top 40 listed JSE shares due to a broader equity income fund perceived as inflation-beating returns, since they receive income in the form of

dividends (Barclays, 2019). Equally so, Switzer (2010) points out that, despite small-cap shares showing growth potential, they are low in liquidity, while mid-cap shares provide less return on investment, with both share types undergoing greater volatility in comparison to a broader market. Lastly, Figure 2.6 details the annual prime rate from 2010 to 2019.

2.5.1.3 Prime lending rate

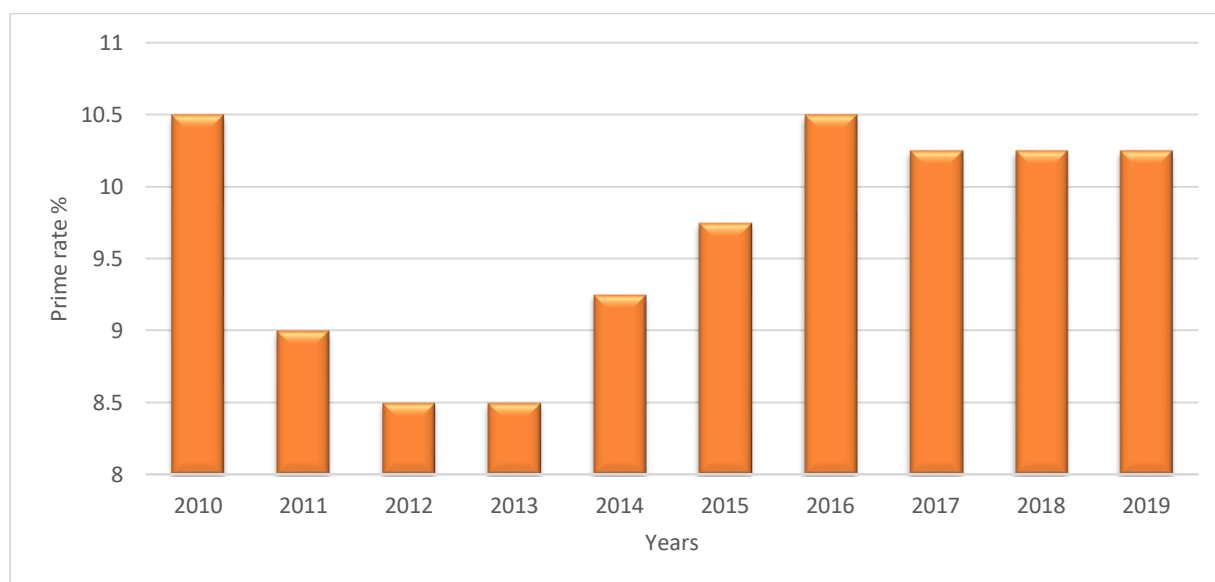


Figure 2.6: Annual prime rate (2010-2019)

Source: SARB (2019)

With the discussion on inflation deteriorating returns on investments, there are two types of interest rates, which play significant roles in this phenomenon. The nominal interest rate, being the rate that is unadjusted for inflation whereby an investor can earn such a rate only if inflation remains at zero (Awomuse & Alimi, 2012). When the inflation rate is deducted from the nominal interest rate, what remains is the real interest rate. It indicates an investor's actual gain or loss of purchasing power (Usbank, 2019). On the other hand, banks are more inclined to lend money to small and mid-cap companies, subject to such companies being charged a certain interest rate that is viewed as a starting point. This rate is then adjusted, based on the specific company risk profile. The rate under discussion is known as the prime lending rate.

SARB (2009) states that a prime lending rate is used by banks to lend out to its creditworthy customers. The South African Reserve Bank sets the starting point of this rate. A high prime rate, as illustrated in Figure 2.6 in the year 2016 at 10.5 per cent, was based on the emphasis that the economy was experiencing slow growth at 0.3 per cent – the worst since the financial crisis (Hogg, 2017). Banks need to protect their shareholders to continue to grow their profit margins, and they

are obligated to make payments to those that have savings accounts. Therefore, lenders charged less in dire economic conditions, in order to discourage high returns (Businesstech, 2016). As described below, investor confidence also declined due to misappropriation of company earnings and investors' investments by company management.

2.5.2 Investor confidence

The lost decade of the JSE small and mid-cap shares was also influenced by the lack of investor confidence, as the economic outlook of the country was experiencing negative growth, as discussed in detail above, having taken into account real GDP, inflation rate, and prime lending rate. Confidence in any investor is well perceived from two elements namely: investor optimism and investor trust (Chandler, 2019). Investor confidence encompassing these two elements can be defined as the willingness to take part in investment opportunities based on risk and return (Ko, 2017), whereas investor optimism entails the ability of investors to make rational investment decisions with an optimistic view of earning good returns. On the other hand, investor trust focuses on putting the best interests of an investor ahead of the company's, to meet the investor's investment goals (Bottazzi *et al.*, 2016).

The underperformance of small and mid-cap shares in the period 2010 to 2019 was based on lack of investor confidence due to unethical and ineffective leadership from the board of directors of companies that were found in financial mismanagement and misstatement of information (Rangongo *et al.*, 2016). Examples of companies that had contributed towards the negative six per cent return in shares in small and mid-cap shares as at 1 March 2019 include: Steinhoff, EOH, Tongaat Hulett, McKinsey & Company, WBHO, Murray & Roberts, and Group Five. These companies had a common characteristic, that they failed to exercise effective and ethical leadership by the governing body in the achievement of ethical culture, legitimacy, effective control, and good performance (Natesan & du Plessis, 2017). Therefore, investor confidence is well aligned with compliance to corporate governance. Although the discussion has been mainly on the lost decade of the JSE, the outbreak of the COVID-19 pandemic has had an impact on small and mid-cap share prices, and the optimal lambda. As a result, previous events on the extreme value theory, and the normal probability distribution are also discussed below.

2.6 EXTREME VALUE THEORY

In statistics and financial risk management, probability distribution is a function that explains the likelihood of various possible outcomes that a random variable can assume (Nadarajah, 2005). Embrecht (2000) points out that within a probability distribution, an extreme value is either a very

small or very large value. It displays a low chance of occurring, but if it does occur, it causes great damage to the economy. Similarly, an occurrence of an extreme event can be costly in financial terms (Longin, 2000). Examples of extreme events are well documented in previous instances. One such event is the 2008 financial crisis, which cost the U.S. economy more than 22 trillion dollars (Melendez, 2013). Another extreme event was the Great Sendai Earthquake, also known as the Japan earthquake and tsunami of 2011 (Maly & Supprasri 2012). The earthquake cost the Japanese economy an estimated 210 billion dollars, which led to suspensions of the manufacturing sector responsible for 20 per cent of the global semiconductor products (Amadeo, 2020). Figure 2.7 illustrates the normal probability distribution.

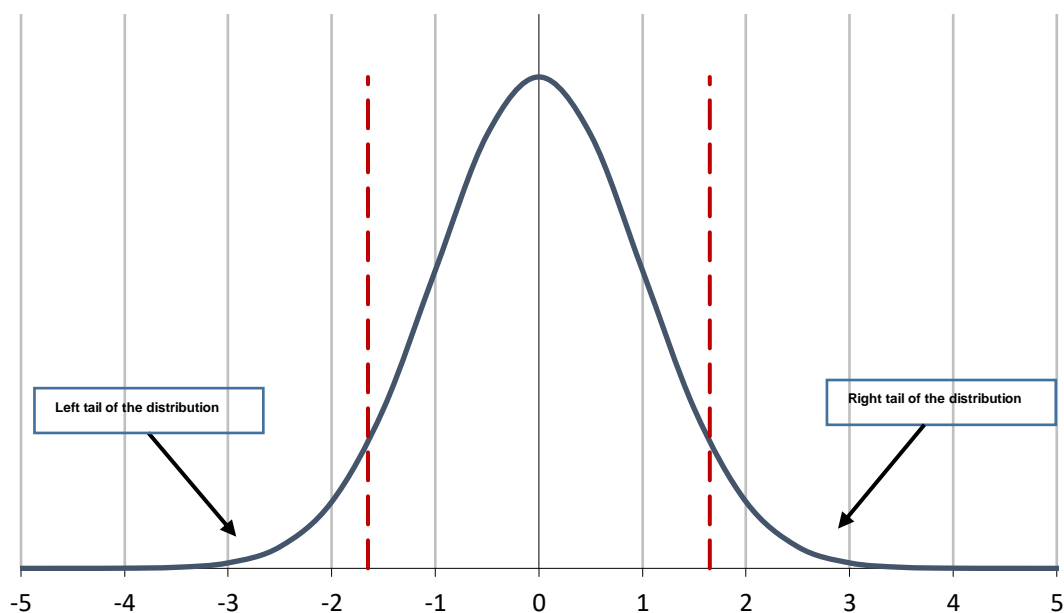


Figure 2.7: The normal distribution curve

The normal distribution explains how the values of a variable are distributed (Vlasenko & Kozlov, 2009). The area in the left and right tail distribution of the normal distribution curve displays the likelihood of extreme values. These values are associated with extreme value theory. The theory is used as a tool to determine risks that are linked with extreme events, while predicting probabilities associated with such extreme outcomes (Diebold *et al.*, 1998). Equally so, it is important to note that the main focus of the extreme value theory is to take into consideration the stochastic behaviour of extreme events in both the left and right tails of probability distributions (Fernandez, 2005). It should also be noted that the extreme value theory and the central tendency in statistics are different. Okten *et al.* (2006) point out that the central tendency is based on the central limit theorem – as the sample size increases, the sampling distribution of the mean approaches a normal distribution. Hence, the extreme value theory is concerned with the behaviour of the left and right tails of probability distributions. Such behaviour is well explained in detail

regarding other extreme events namely: the Severe Acute Respiratory Syndrome (SARS) outbreak of 2003 and the outbreak of COVID-19.

Severe Acute Respiratory Syndrome (SARS) is the name of the respiratory illness, which is caused by SARS-COV (Zhong *et al.*, 2003). Meanwhile, coronaviruses are a large family of viruses, which have a large host range, including humans (World Health Organisation, 2020). Feuer (2020) states that even though both viruses originated in China, it is speculated that COVID-19 will have a greater impact on the global economy, in comparison to the SARS outbreak. The SARS outbreak cost the global economy 40 billion dollars (White, 2020). On the other hand, COVID-19 is estimated to have cost the global economy at least 1 trillion dollars in the year 2020 alone (World Economic Forum, 2020). What these outbreaks share in common is that they originate in one point and spread globally. They exhibit a trait of being unusual events that, to an extreme, have a low chance of occurring but once they do, they lead to great damage to the economy (Analyst Prep, 2019). However, the type of recovery from the impact of the COVID-19 outbreak is yet to be determined. The SARS outbreak underwent a V-shaped recovery during a recession. A V-shaped recovery is a sharp downturn, which is followed by a rapid rebound in growth (Yao, 2011). The likelihood of a similar recovery happening with COVID-19 will see the economy rebounding quickly.

Since the extreme value theorem places emphasis on events leading up to extreme values, as discussed concerning outbreaks such as COVID-19 and SARS, the lost decade of the JSE can be placed in this category. As already discussed, the lost decade of the JSE in small and mid-cap companies was a period in which macroeconomic factors partially resulted in failure to comply with corporate governance (Pitro, 2019). The occurrence of such an extreme event is very rare and has proven to be costly in financial terms, as the share prices declined significantly from 14 per cent in 2010 to negative 4 per cent in 2019 (Van Vuuren, 2019). It is probable for such an event in small and mid-cap companies to occur in the future, to the detriment of small and mid-cap companies. Hence, it is important to make use of the EWMA and GARCH (1, 1) models to forecast the volatility of small and mid-cap shares. These models, used as measurements of volatility forecasting, are explained in the following section.

2.7 PREVIOUS LITERATURE ON VOLATILITY FORECASTING

Although volatility forecasting has been widely researched using extended GARCH models namely the competing univariate GARCH models, these models, including the GARCH (1, 1) model used in this study, take into account the GARCH-M (1, 1), EGARCH (1, 1), GJR-GARCH (1, 1), and the APGARCH (1, 1) models (Kgosietsile, 2014). The models were compared to each

other, based on competitiveness to best describe out-of-sample realised volatility and the inclusion of the South African Volatility Index, as it was also used in volatility forecasting (Kgosietsile, 2014). Previous studies, in alignment with this study, forecasted volatility using historical time series data with models used as the EWMA and the GARCH (1, 1). Previous studies were based on the entire stock market and not specifically on the small and mid-cap shares.

Nilakantan & Mistry (2013) forecasted the volatility of the Indian Stock Exchange using historical daily data during the period 1 January 2003 to 31 December 2012. The study did not analyse the optimal lambda during the period, since it mainly focused on comparing and depicting the more preferable model between the EWMA and GARCH (1, 1). The GARCH (1, 1) model was preferred during short term horizons, as it takes into account mean reversion as a property of volatility. However, due to its disadvantage, being that it is unable to model asymmetries of volatility about previous share price shocks, the study acknowledged various GARCH models that can model asymmetries, while considering the leverage effect as another property of volatility (Nilakantan & Mistry, 2013).

Ding & Meade (2010) forecasted the accuracy of stochastic volatility, using the GARCH and EWMA models under various volatility scenarios. The study was aimed at identifying volatility scenarios that were inclined with the GARCH, stochastic volatility, and EWMA models. The stochastic volatility models provided more accuracy than the GARCH and EWMA models in scenarios where the volatility of share prices was very high. Ding & Meade (2010) further put forward that the EWMA model provided more accuracy and flexibility in forecasting than the GARCH model. On the other hand, Ladokhin (2009) analysed difficulties of choosing the best model to forecast volatility in the stock market, using various models, including the historical average model, which is regarded as simple to implement, yet yielded underwhelming results. Contrary to expectations, the models that were robust to implement, such as the implied volatility method yielded better results. Nevertheless, Ladokhin (2009) argues that both the historical average and implied volatility methods, provided no guarantees of being perfect approaches.

Miah & Rahman (2016) analysed the performance of the GARCH (1, 1) model against other aforementioned versions of the model for the period 1 January 2000 to 30 November 2014. It was found that the GARCH (1, 1) model

was more preferable than the others in modelling volatility for the daily returns of the Dhaka Stock Exchange. The results also depicted the stock exchange share price return featuring volatility clustering. On the other hand, Kayahan & Memis (2014) made comparisons of the EWMA and GARCH models in estimating the exchange rate volatilities. Based on the test called the root mean

square, whereby smaller values are preferred, the EWMA model provided more accurate estimates than GARCH (1, 1) in the euro against the Turkish lira, using the root mean square error test, and the results were 0.0665 and 0.0652, respectively. Meanwhile, in the British pound against the Turkish lira, using the GARCH (1, 1) and EWMA for a similar test, the results were 0.0668 and 0.0637, respectively (Kayahan & Memis, 2014). The aforementioned previous studies were not centred on extreme events as their main important consideration, however, the great Sendai earthquake that took place in 2011 in Japan, was considered an extreme event, which affected the Japanese financial market (Fakhry *et al.*, 2018).

In the analysis for share price volatility, the C-GARCH-t model was used and the competitiveness of the Japanese financial markets was in scrutiny. The C-GARCH-t model was used to differentiate the long and short term impact of the sendai earthquake on the effectiveness of the Japanese financial market. The results using the C-GARCH-t model indicated that the impact of the great sendai earthquake on the Japanese financial market revealed a financial market that operated partly efficient. A partly efficient financial market showcased that the Japanese financial market was an inefficient market (Fakhry *et al.*, 2018).

Overall, previous studies mainly focused on stock exchanges than on small and mid-cap indices, meanwhile, extreme events were also not their prime concern with an exception of the 2008/09 financial crisis which affected the world economy. This leaves much room for analysis in the context of the small and mid-cap share returns and the COVID-19 extreme event.

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CHAPTER 3: RESEARCH ARTICLE 1

VOLATILITY FORECASTING DURING EXTREME MARKET EVENTS USING THE SMALL-CAP SHARE INDEX

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ABSTRACT

The period 2010 to 2019 is known as the lost decade of the JSE in small-cap companies as a result of a decline in investments, due to the high risk of investing in small-cap shares. For this purpose, the study aims to use the EWMA and GARCH (1, 1) models to forecast volatility of share price returns at the end of day $n-1$. The study also aims to determine the optimal lambda by 31 July 2020. This was amid the extreme event COVID-19 which negatively affected small-cap shares. A negative relationship between share price returns and volatility in small-cap shares was encountered throughout the 21-day COVID-19 lockdown introduced by the South African President, Cyril Ramaphosa. A comparison was made between the models and the use of the small-cap index (J202) was applied. The models highlighted the key weakness of the standard deviation, assigning the same weight to all share price returns in the period under analysis. The models captured share price shocks on December 2015, as a result of heightened political risk.

JEL: G01, G11, G17

3.1 INTRODUCTION

Small capitalisation shares are more domestically exposed businesses, which derive their large portion of profits within the boundaries of South Africa (Bergman, 2019). This brings to light their vulnerability towards economic tensions from which they are not immune. They are more affected by changes in the economic environment (Thune, 2020). Besides, they are at risk from global economic recessions. During the burst of the dotcom bubble in 2002, and the financial crisis in 2008, the performance of small-cap share index against the Johannesburg Stock Exchange (JSE) Top 40 Index was at negative 67.80 per cent and negative 32.68 per cent, respectively (Friedrich, 2019). In both instances, there was a significant sell-off in small-cap shares as a result of investors pushing towards the diversification of their investment portfolios amongst large-cap shares. Mtemeri (2019) makes a definite point on the benefits of dual listing by large-cap shares from the investors' perspectives, such as taking advantage of two varying markets with different investment opportunities based on risk and return. In addition, dual listing is viewed as an opportunity for diversification.

Nonetheless, in both instances of the dotcom bubble in 2002 and the financial crisis in 2008, small-cap shares tended to outperform the large- and mid-cap shares much faster after each economic

downturn (Switzer, 2010). Thune (2020) highlights that during this period, small-cap companies sold their undervalued shares to raise capital, while large-cap companies borrowed capital through the issuing of bonds. Once again, in March 2017, small-cap companies listed on the JSE performed at negative 38.90 per cent, and this was an opportunity realised by investors to invest in better-quality small-cap shares (Friedrich, 2019). Likewise, South African Market Insights (2019) defines the economic progress index as an index that measures the progress in the growth of the South African economy. The economic progress index declined by negative 20.2 per cent from 2010 to 2018 (South African Market Insights, 2019). Lipper (2020) argues that besides the economic progress index, investors with appropriate time horizon only buy small-cap shares on the basis of their inexpensiveness, not on the guarantee of higher returns.

Investors can benefit immensely from fundamental analyses by competent management teams. When investors focus solely on valuation, they expose themselves to possibilities of being invested in companies that assign the same weight to their shares. Such companies can also be inconsiderate of modelling share volatility forecasting based on the EWMA and GARCH (1, 1) models. Additionally, Bollen (2015) explains that the factoring in of lambda as a decay factor, also known as a smoothing parameter is important in determining exponentially decreasing weighting schemes of the observed data in which a high optimal lambda will indicate a slow decay in the analysis, thus, implying a high variance persisting for a long period. The objective of this article is, therefore, to examine the EWMA and GARCH (1, 1) models when forecasting volatility in small-cap shares using the small-cap index (J202). The study also seeks to investigate the models' relationship to the use of daily data and analyse whether COVID-19 can be categorised as an extreme event while calculating the optimal lambda for the period under analysis, which will be recognised in the respective models.

3.2 LITERATURE REVIEW

Before investors decide to make a purchase of shares from companies listed on the JSE, it is important for them to know the various index categories and how the companies that are listed in these categories vary on the basis of their market capitalisation. According to Panagiotidis (2005), market capitalisation makes it understandable for an investor to determine a company's size in assessing the risk of investing in its shares. Thus, it is the total market value of a company's outstanding shares (Khrawish *et al.*, 2010). Likewise, small-cap companies have a market capitalisation that is below one billion Rand (JSE, 2020). Wyatt (2009) states that small-cap companies should not be confused with start-up companies. Small-cap companies have moved past the start-up phase since they were able to establish themselves by being publicly traded and owned

entities through the initial public offering (IPO). However, small-cap companies tend to be overlooked by the Top 40 Index, which consists of companies that are investable on the JSE, as it is favoured among investors that earn higher returns when selling the most shares.

The small-cap index is a representative of 96 per cent to 99 per cent of the full market cap value of all qualified ordinary securities that are listed on the main board of the JSE (JSE, 2020). The index is fairly overlooked since it is particularly unfavourable among investors because of its high level of volatility and lack of extensive history (Eun *et al.*, 2008). Small-cap companies have made their initial impact in their respective industries, which placed them on the stock exchange. They are set to grow and have a big impact in the coming years. For that reason, an investor that considers small-cap shares will benefit from the following advantages. Van Vuuren (2019) points out that on average, companies listed in the Top 40 Index consist of eleven research analysts covering each company, while there are approximately two analysts in small-cap companies. Imbert (2019) states that this creates an investment opportunity for potential investors that are willing to conduct thorough research on undervalued shares.

Although large- and mid-cap shares provide an investor with attractive returns, given the level of risk to which they are exposed, small-cap companies should be perceived as long-term investments (Thune, 2020). Due to their reputation of being more volatile, while steadily building and diversifying their investment portfolios, the former companies have a fair probability of yielding returns that are greater than those of the latter. There is less competition when buying small-cap shares, as their market is smaller than that of the large and mid-cap shares (Reyes, 2001). Buying shares during the initial public offering implies that their value will increase as the company gains popularity with investors, as well as its own reputation. Equally so, Tinic (1988) adds that, in the long run, an investor will potentially gain a high return on investment. Small-cap companies take advantage of their efficiency and effectiveness since large-cap companies have many employees and various layers of management that they report to namely: a large number of people on the board of directors, which can extend to 31 members (Reddy *et al.*, 2008). This hinders the large-cap companies' decision-making processes. However, small-cap companies are in a position of implementing new strategies quickly, given that they have small boards of directors of approximately seven to fifteen members (Natesan & du Plessis, 2018). In the interest of having a balanced understanding of small-cap shares, the companies in this category encounter the following disadvantages.

Even though small-cap companies outperform large- and mid-cap companies during economic recoveries, their vulnerability to economic downturns due to less financial resources leads investors to opting for small-cap mutual funds and Exchange Traded Funds (Bontis *et al.*, 2007).

This option helps to lower the risk of loss. In comparison to other companies, their high level of risk due to high volatility might make it difficult for investors to invest hence; diversifying an investment portfolio by having a small percentage of small-cap shares can turn out to be useful (Eun *et al.*, 2008). There is no guarantee that these companies will break into the Top 40 Index and pay dividends (Schwartz & Zimmer, 2013). Instead of making dividend payments, small-cap companies make use of their profits for growth. Menkveld & Wang (2013) deduce that these companies tend to have fewer outstanding shares, thus, creating a liquidity problem.

Investors holding shares could find it challenging to find buyers to unload their shares to, since the market is volatile (Cacheche *et al.*, 2015). The optimal liquidity theory supports this phenomenon. It states that as assets or market liquidity increase, their risk decline to a point in which the increased liquidity attracts an adequate number of speculators to offset the lower risk and, ultimately, increase the risk of the asset or market (Han & Lee, 2012). Therefore, there is an optimal point in which maximum liquidity is reached. This point is known as optimal liquidity. It is best illustrated in Figure 3.1 below.

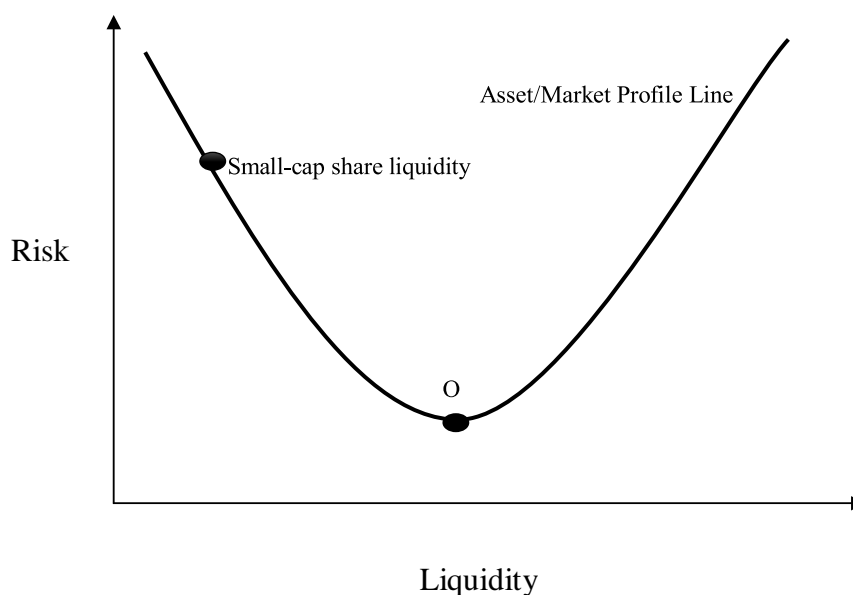


Figure 3.1: Optimal liquidity

The above theoretical figure illustrates the optimal liquidity and small-cap share liquidity. In support of the optimal liquidity theory, as an asset or market liquidity increases, a decline in the risk profile occurs up to an optimal point whereby maximum liquidity is reached. However, increasing liquidity of an asset attracts traders to speculate in the asset or market. On the other hand, small-cap shares are in general less liquid, more volatile, and overall risk of shares. Chen *et al* (2009) make a definite point on the issuance of mispricing as they tend to occur whereby they lead to difficulties in determining the actual share price.

Investors in small-cap shares may attempt to maximise their gains by identifying shares that are mispriced. Under this premise, Friedrich (2020) dismisses the theory of an efficient market, which states that all information regarding shares and investment securities is included in their respective prices (Thune, 2020). There are three forms of efficient market hypothesis namely: weak, semi-strong, and strong. The weak form implies that all previously held information is priced into securities and, as a result, technical analysis of past share prices in outperforming the market cannot be used. Meanwhile, the semi-strong form suggests that new and recent information is priced into securities, whereby neither fundamental nor technical analysis can be used in achieving abnormal returns (Thune, 2020). The strong form implies that both public and private information is priced into shares and that investors cannot have an advantage of the entire market (Ball, 2009). As small-cap shares tend to outperform both the mid- and large-cap shares, they pose a challenge to the strong form of the efficient market hypothesis.

The abovementioned challenge supports the small company bias theory, which states that the shares of small-cap companies earn abnormal returns and outperform mid- and large-cap companies (Simonson, 2014). This occurrence is often overlooked since small-cap companies are rarely prioritised in comparison to their counterparts. This gives rise to the neglected firm effect, which explains the notion of small companies outperforming better-known companies due to their higher risk and reward potential (Akhter *et al.*, 2015). The negligence is well explained particularly in the extreme event of the outbreak of the global coronavirus pandemic or commonly referred to as COVID-19. Thereby providing an opportunity for investors with a long-term horizon (Friedrich, 2020). Friedrich (2020) explains that, as at 16 June 2020, the small-cap index was down by 18 per cent since the commencement of COVID-19, in comparison to a decrease of 9 per cent for the JSE all-share index. This illustrates the high risk of investing in small-cap shares. Despite this, such risks are manageable, as they create openings for capitalising on such mispricing opportunities (Gilbert, 2019).

Since small-cap companies have smaller earnings, they make way for better growth potential, as in the case of Capitec Bank, which started as a small-cap and became the third largest bank in South Africa (Vermeulen, 2018). Capitec Bank reported consistently strong financial results for the period ending February 2020 with earnings increasing by 19 per cent to 6.28 billion rand (Capitec Bank, 2020). The growth is largely due to a strong client growth, with over 2.5 million new clients. The bank scored 84.0 for customer satisfaction, ahead of Nedbank, and FNB, whose scores stood at 80.2 and 79.9, respectively (Consulta, 2020). On the other hand, Figure 3.2 illustrates the behaviour of the small-cap share prices of the Top 40 share prices during the financial crisis in 2008.

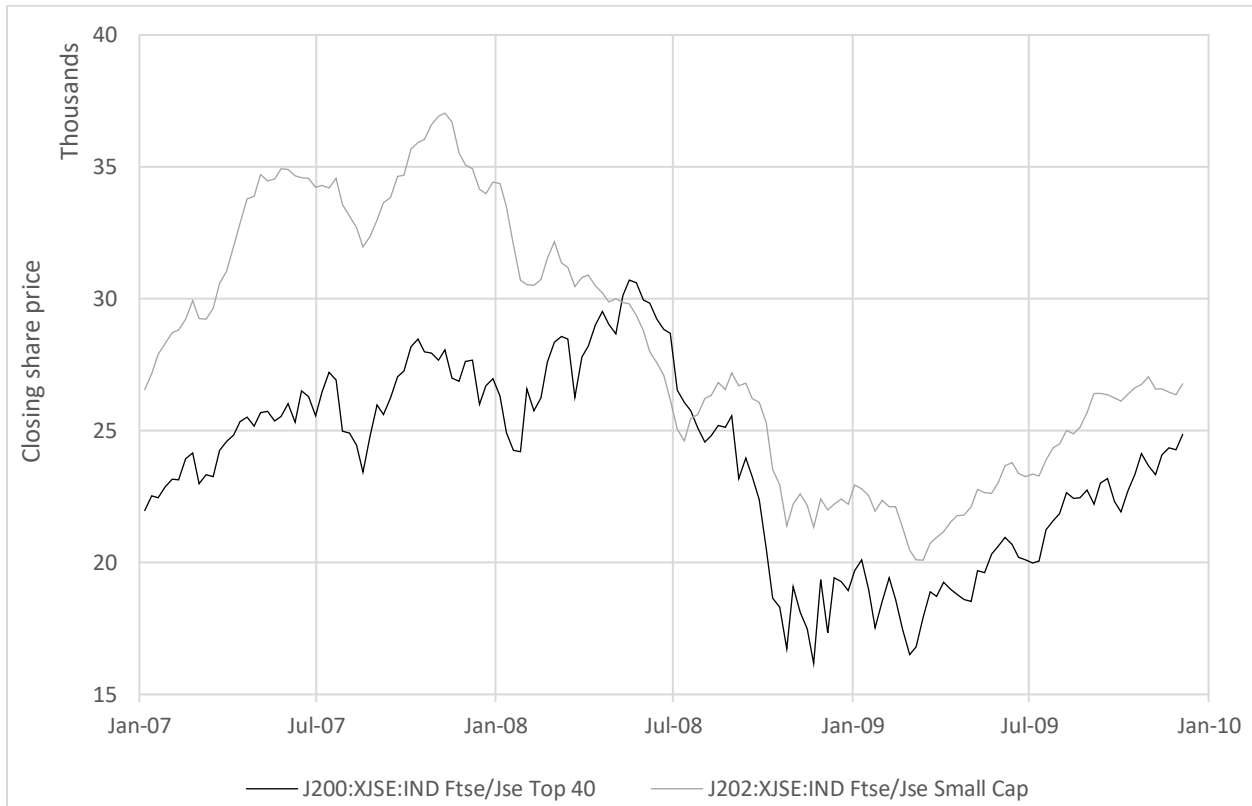


Figure 3.2: Behaviour of small-cap share prices against the Top 40 companies during recessions and recoveries

Source: IRESS INET BFA (2020)

Figure 3.2 illustrates the performance of the share prices of the JSE Top 40 and small-cap companies. During the period 10 November 2007 and 25 October 2008, small-cap shares were at 370.36 rand and 213.78 rand, respectively. Small-cap shares have undergone a negative percentage change of 42.28 per cent. In the same period, Top 40 shares were at 280.54 rand and 167.24 rand, respectively. Top 40 shares experienced a negative percentage change of 40.39 per cent. From this, the small-cap shares experienced a significant price decline, so did the Top 40 shares. However, in theory, small-cap shares tend to rise faster than large-cap shares during economic recoveries (Hulbert, 2020). Figure 3.2 supports the theory, as in the year 2009 the shares in the small-cap companies were trading higher than those of the Top 40. Gurdus (2020) argues that the rapid rise in recovery for small-cap share companies is based on the fact that, having undergone a steeper decline in a recession, their shares tend to be undervalued. Small-cap shares get a performance reinforcement, as they present attractive valuations when they are acquired and merged with large-cap companies that are looking for ways to grow. Nevertheless, the riskiness and high volatility in small-cap shares should be taken with caution.

The great recession of 2008 began in 2006, due to the significant decline in housing prices in the United States of America, which was referred to as the subprime mortgage crisis (Vieira, 2011). By the third quarter of 2008, the GDP of USA declined by 0.3 per cent (Bureau of Economic Analysis, 2008). This occurred in the wake of the subprime crisis, which adversely affected the country's economy. By September 2008, the Dow Jones Industrial Average dropped 777.68 points in intra-day trading, the high rate in the decline was caused by the Congress's refusal to adopt the Bank Bailout Bill (Perman, 2008). Both the subprime crisis and the crash in the New York Stock Exchange fuelled the recession, a financial crisis that spilt over to the world economy. Maredza & Ikhide (2013) point out that South Africa was not exempt from the negative effects of the global financial crisis. The economy declined by 1.8 per cent in the fourth quarter of 2008 (Marais, 2009).

3.3 METHODOLOGY

The financial data that were used for analysis in this study were obtained from an online tool named IRESS INET (Pty) Ltd. The study made use of daily data for the period 01 January 2010 to 31 July 2020. 01 January 2010 was chosen as a starting period because 2010 was the year in which shares in small and mid-cap JSE-listed companies began to experience a significant decline. The date 31 December 2019 was when the share prices, at negative four per cent, were at their lowest in the decade. The period was extended to 31 July 2020 for the inclusion of the extreme event namely: the outbreak of COVID-19 global pandemic, and its effect on the optimal lambda. It was followed by the analysis of the financial crisis, and the impact of the ousting of the South African former Minister of Finance, Nhlanhla Nene towards the economy while determining the optimal lambda of small-cap share volatility.

The use of daily returns for analysis was based on the assumption that volatility-based information was likely to be lost at lower frequencies, particularly in periods of a crisis (Danielsson *et al*, 2018). Hence, Ederington & Guan (2005) pointed out that when using daily data, both the EWMA and GARCH (1, 1) models performed better, with a more accurate forecast of the volatility after day $n-1$. The methodology took into account the current volatility, which is based on historical data, using the EWMA and GARCH (1, 1) models. But first, it was important to derive these models in order to get an understanding of the analysis.

3.3.1 FORECASTING VOLATILITY

The EWMA and GARCH (1, 1) models were derived, read and chosen because they provided solutions to the research question which stated the manner in which investors will benefit from holding shares based on the specified models outcome, meanwhile, highlighting volatility and

optimal lambda at the end of the study analysis period, 01 January 2010 to 31 July 2020. Thus, the two models are ideal for the achievement of the empirical objectives of the study. This study derived both models in the following manner:

The symbol σ_n was defined as the volatility of a share price on day n, as forecasted at the end of day n-1. The square of the volatility, σ_n^2 on day n was the variance. Using the historical data, this was forecasted in the following manner:

The value of a share at the end of day i was S_i . The variable u_i was the continuous compound return between the end of day $i - 1$ and the end of day i which gave the following equation:

$$u_i = \ln\left(\frac{S_i}{S_{i-1}}\right)$$

The square of the volatility σ_n^2 using the most recent m observation on the u_i to have a fair estimate of the variance per day was provided with this equation:

$$\sigma_n^2 = \frac{1}{m-1} \sum_{i=1}^m (u_{n-i} - \bar{u})^2 \quad (3.1)$$

Whereby \bar{u} symbolised the mean of the u_i 's:

$$\bar{u} = \frac{1}{m} \sum_{i=1}^m u_{n-i}$$

Since the analysis was based on daily volatility, the above formula was changed based on the assumption that \bar{u} was zero and $m - 1$ was replaced by m .

u_i was the percentage change in the share price between the end of day $i - 1$ and day i which allowed

$$u_i = \frac{S_i - S_{i-1}}{S_{i-1}} \quad (3.2)$$

Even though these changes contributed small changes to the estimate calculated, they simplified the formula for the variance to be as follows:

$$\sigma_n^2 = \frac{1}{m} \sum_{i=1}^m u_{n-i}^2 \quad (3.3)$$

Whereby u_i was provided in (3.2).

3.3.2 WEIGHTING SCHEMES

Though equal weight was provided to the m observations as depicted in the above equation, the current level of volatility (σ_n) was of interest in forecasting and more weight was provided to recent data.

The formula derived at 3.3 will then be revised to the following weighting scheme

$$\sigma_n^2 = \frac{1}{m} \sum_{i=1}^m \alpha_i u_{n-i}^2 \quad (3.4)$$

The variable α_i was defined as the amount of weight that was provided to the observation i in previous days. The value of α (the weights) was positive (Nilakantan & Mistry, 2013). A long-run variance (V_L) and its weight (γ) is assigned and it transforms the model to a new form which is as follows

$$\sigma_n^2 = \gamma V_L + \sum_{i=1}^m \alpha_i u_{n-1}^2 \quad (3.5)$$

As suggested by Engle (1982), the above formula was an ARCH (m) model. The long-run variance (V_L) and its weight (γ) were replaced by the symbol ω .

$$\sigma_n^2 = \omega + \sum_{i=1}^m \alpha_i u_{n-1}^2 \quad (3.6)$$

According to equations (3.4) and (3.6), two approaches were developed to monitor volatility. These approaches are the EWMA and GARCH (1, 1) models.

The EWMA was the model applied in equation (3.4), whereby weights α_i declined exponentially when moving back in time. In particular, α_{i+1} was defined as $\lambda \alpha_i$ whereby λ was a constant between zero and one. Such a weighting scheme was simplified with a formula for volatility forecasting, which is as follows:

$$\sigma_n^2 = \lambda \sigma_{n-1}^2 + (1 - \lambda) u_{n-1}^2 \quad (3.7)$$

The forecast of the volatility (σ_n) of a variable for day n (made after day n-1) was calculated from σ_{n-1} (the forecast that was made after day n-2 of the volatility for day n-1) and u_{n-1} (the foremost recent daily rate change within the variable).

The EWMA approach was designed to track changes within the volatility (Adewuyi, 2016). If there was a huge move within the market variable on day n-1, and u_{n-1}^2 was huge, as depicted in equation (3.7), the forecast of volatility was moved upward. The value of λ administered how responsive the forecast of the daily volatility was subject to the foremost daily percentage change (Finance Train, 2020). On the other hand, a higher weight was provided to the u_{n-1}^2 when volatility (σ_n) was calculated, as such, the value of λ declined. Furthermore, as λ got closer to one, its value increased whereby it led to the forecast of daily volatility that reacted moderately slower to data recently provided by daily percentage change.

The value of λ provided forecasts of variance that were near the approach to the realised variance rate. The value of the optimal lambda was determined. Meanwhile, the EWMA model was simply a non-stationary version of the GARCH (1, 1) model in which the parameters, namely, α_1 and β_1 , added up to the value of one.

Regarding the GARCH (1, 1) model, the variance (σ_t^2) was fundamentally calculated from the following: the long-run variance (V_L), σ_{n-1} and u_{n-1} . The formula for volatility forecasting concerning the GARCH (1, 1) model took the following form:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (3.8)$$

The symbol γ implied the weight assigned to V_L , whereas, α was the weight provided to u_{n-1}^2 and β was the weight provided to σ_{n-1}^2 . The weights added up to unity, resulting in the equation $\gamma + \alpha + \beta = 1$.

For the weights that added up to one based on the GARCH (1, 1) model, the following was different as the EWMA model weights were as follows: $\gamma = 0$, $\alpha = 1 - \lambda$, and $\beta = \lambda$. Since the variance (σ_t^2) was based on the most recent observations of u^2 and the latest forecast of the variance rate, the (1, 1) in the GARCH model was determined. The weight provided to V_L was written as ω . Hence, the GARCH (1, 1) model was rewritten as follows:

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (3.9)$$

Once the parameters (ω , α , and β) were forecasted, the weight assigned to V_L was calculated such that $\gamma = 1 - \alpha - \beta$. To ensure the GARCH (1, 1) model was stable in the analysis, there had to

be a condition put in place whereby the sum of the parameters (α, β) was less than one i.e. $\alpha + \beta < 1$. When the sum of the parameters (α, β) was greater than one, a negative weight imposed to the long term variance was reflected i.e. $\alpha + \beta > 1$ (Nilakantan & Mistry, 2013). In addition to the negative weight, the GARCH (1, 1) model was reduced to the EWMA model such that the sum of the parameters (α, β) was equal to one i.e. $\alpha + \beta = 1$. At this point, the weights experienced an exponential decline at the rate β . The parameter was also referred to as a decay rate (Collins, 2020). It reacted similarly to λ in the EWMA model. It was responsible for its importance towards the observed u 's (percentage changes in share prices) in calculating the current variance. The difference between the two models was based on the manner in which the GARCH (1, 1) model allocated weights towards the long-run variance volatility and from the analysis, the more preferable model was determined.

3.4 RESULTS AND DISCUSSION

The historical standard deviation assigning the same weight to all share price returns in the period regarded as the lost decade of the JSE is its key weakness (Milton, 2019). This study aimed to realise how investors can benefit from investing in small-cap shares by analysing share price returns using the EWMA and GARCH (1, 1) models, respectively. The EWMA model was constructed against the historical standard deviation, while the GARCH (1, 1) model was also analysed against the historical standard deviation.

Small-cap shares are volatile, and they are simply regarded as highly risky investments because they fluctuate more than other share investments in mid-cap or large-cap companies (Imbert, 2019). Since volatility is a statistical value that considers the range of returns for a given share price, it measures this dispersion through the standard deviation between returns (Campbell & Lettau, 1999). On the other hand, the EWMA model, as a weighted average of past volatility considers the persistent and clustering of volatility, thus, implying that a period of high volatility is followed by a period of high volatility (Cont, 2007). In the same way, a period of low volatility is followed by a period of low volatility. Following the theoretical objective which proposes the contextualisation of the significance of volatility forecasting of asset returns in small and mid-cap shares to investors, the EWMA and GARCH (1, 1) models' volatilities provide a broader understanding of the construction of share investments than solely focusing on the standard deviation. The following figures illustrated the execution of empirical objectives, as stated in the study objectives in Chapter 1. Ten companies were selected as a sample and analysed for the period 1 January 2010 to 31 July 2020 in determining the optimal lambda. The companies were City

Lodge Hotels, Adapt IT Holdings, EOH Holdings, MC Mining, Nampak, Purple Group, Sasfin Holdings, Adcorp Holdings and Tongaat Hulett.

Table 3.1: Optimal lambda for small-cap shares

Small-cap companies	City Lodge Hotels	Adapt IT Holdings	EOH Holdings	MC Mining	Nampak	Purple Group	Sasfin Holdings	Adcorp Holdings	Netcare	Tongaat Hulett
Phi	10.38%	0.05%	6.14%	0.18%	14.56%	0.07%	6.27%	5.35%	29.70%	27.31%
Lambda	0.985	0.988	0.988	1.000	0.962	0.955	0.958	0.808	0.898	0.936
Optimal lambda	0.931									

Table 3.1 made provision for determining the optimal lambda of small-cap shares within a sample of small-cap companies. The weight applied to the recent share price return on 31 July 2020 was determined by adding the phi and lambda of each company in which the decay factor for daily data reflected as the optimal lambda of 0.931, also known as a smoothing constant, used in determining the exponentially declining weighting scheme of the observations in the sample period. A low lambda indicated a rapid decay in the series to which a substantial instability in the market led to high volatility, as it was evident following the outbreak of COVID-19 as an extreme event in the case of the optimal lambda.

Despite this, it was considered that there was a negative relationship between volatility and share price return, when forecasting volatility for small-cap shares as they were less liquid and more volatile. Small-cap shares were generally viewed as an overall risk for investment. Forecasting with historical daily data was made for one day following the end of the period under analysis. This implies that the forecast was made by 31 July 2020.

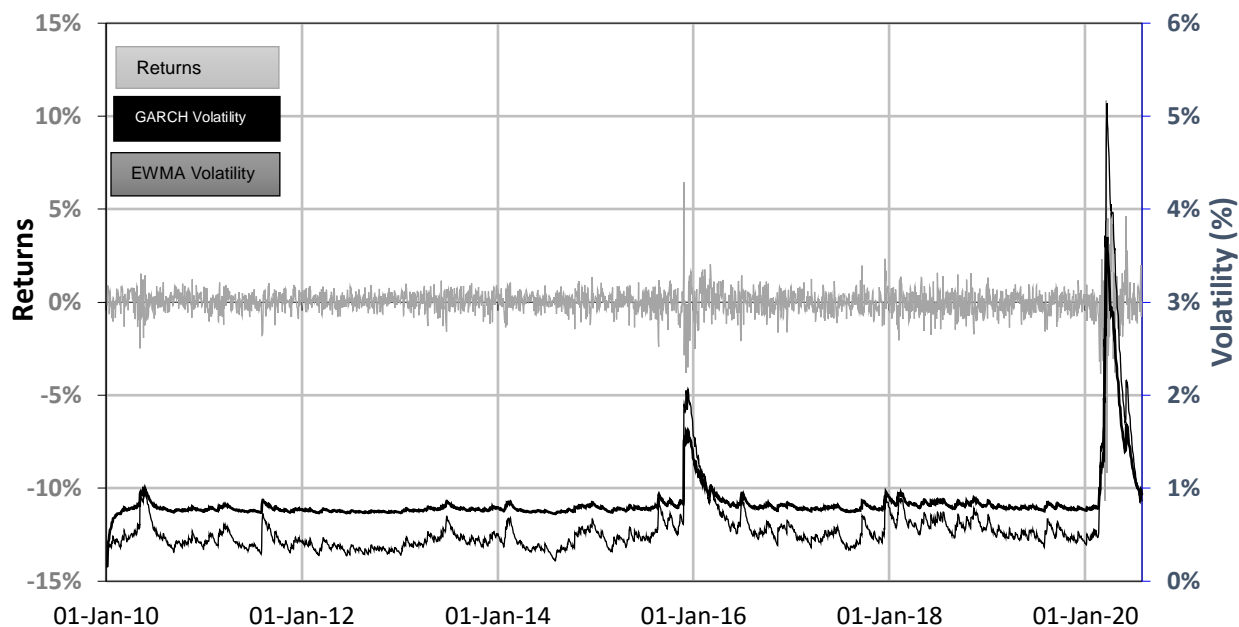


Figure 3.3: Comparison of EWMA and GARCH (1, 1) volatilities for small-cap shares

The EWMA and GARCH (1, 1) models track a relatively similar movement of the volatility of small-cap shares. The distinction between the models lies in the components that make up each equation. The EWMA model considers the optimal lambda expressed as 0.931 for daily data. It was appropriate to make use of 0.931, as data were depicted daily. The forecast of volatility for day n (made at the end of 5 January 2010) was calculated by taking the previous day's volatility (σ_{n-1}) and present-day share price return (negative 0.16 per cent) and the optimal lambda of 0.931 for daily data using the equation $\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1 - \lambda)u_{n-1}^2$. A similar principle was applied to share prices that followed, up to 31 July 2020 for forecasting. The value 0.931 did the following to the equation and the overall model, it controlled how reactive the forecast of daily volatility was to the leading daily percentage change.

By changing the value 0.931 to a declining value, approaching zero, more weight was assigned to recent share price returns while less weight was assigned to distant share price returns. On the other hand, increasing the value 0.931 closer to one, share price returns were equally weighted. The change in the value 0.931 is at the centre of EWMA volatility and weights of share price returns. Either the change of the value 0.931 or the weight of all share price returns amounted to 100 per cent with an exception of having the value at one. In that regard, all share price returns remained at zero per cent and EWMA volatility remained at constant volatility of an absolute value of 0.16 per cent. Using 0.931 share price return weights declined exponentially, which was a feature applied to the model to make aware of the historical standard deviation assigning the same weights to all share price returns in the sampling period. The application of the GARCH (1, 1) model was due to noting the variation between its outcomes to that of EWMA. Conversely, the EWMA model

suffered from recovering slowly from large share price shocks, whereas GARCH (1, 1) model reacted quickly in recovering from similar large share price shocks (Malz, 2020).

The GARCH (1, 1) model considered three distinct weights. Gamma, which is a weight assigned to the long-run variance (V_L), took the value of 0.0345. Alpha is the weight assigned to the previous day's squared return as day n-1 (u_{n-1}^2), which makes up the value of 0.0345, as well as beta, as the weight assigned to the previous day's variance as day n-1 (σ_{n-1}^2), taking the value of 0.931. The value 0.931 was yet used, as EWMA is a non-stationary type of the GARCH (1, 1) model, whereby all three weights add up to one. Volatility forecast for day n (5 January 2010) was calculated by considering the previous date (4 January 2010) and the share price return of 5 January 2010 at negative 0.16 per cent. The weights for daily data were factored in the equation $\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$. The equation was recursive as the present-day volatility was forecasted. The same structure of the calculation of forecasting volatility was followed up to 31 July 2020.

In addition to assigning exponentially declining share price weights, the long-run variance was modelled in a way that the series tended to gravitate or pull towards (Carvalho et al, 2018). The product of the long-run variance of one per cent squared and gamma weight led to the value of omega 0.00000345. The weights declined exponentially as greater share price weights were assigned to recent dates and lesser share price weights were assigned to more distant dates. Moreover, the weights of the share price returns amounted to 100 per cent. Even with the shared characteristic of exponentially declining share price weights, the GARCH (1, 1) model could readjust quickly to the repercussions of share price shocks (Blasques *et al*, 2017). Following the share price shock on 11 December 2015, the GARCH (1, 1) model had a more constant fluctuation in volatility, while the EWMA model was infrequent in the fluctuation of volatility as it captured more share price shocks. In both instances, the value 0.931 contributed a major role to the equations that made up each model.

The presence of the EWMA and GARCH (1, 1) models provided a well-explained phenomenon behind investing in small-cap shares. These types of shares were known to emulate the low cost of entry when compared to the issuance of mid- and large-cap shares (Jooste, 2019). The relatively low share prices were due to low demand in the market. This followed the performance of small-cap shares during economic uncertainty. Such an occurrence was well captured by the short-term shock in the price volatility which took place on 11 December 2015. During this period of economic uncertainty, investors tend to be uncertain about the performance of these companies and this created widespread panic, which led to the selling of shares while a share market downtrend took place (Stevens, 2020). Both models were able to forecast the highest volatility in

the sample period on 11 December 2015. Meanwhile the lowest return in shares on the same date was depicted. This was of great importance towards the negative volatility-return relation.

As short-term share volatility is a result of news effect or economic uncertainty, it gives rise to political risk – the risk investment in share return could undergo due to political instability in a country (Lensink et al, 2000). Share price returns plunged at a low of negative 3.50 per cent. The news effect was due to the ousting of the former finance minister Nhlanhla Nene (Letsoalo, 2015). The negative return associated with increased volatility is an adapted principle, which helps in distinguishing the relations between volatility and returns. When short-term volatility increases, it is followed by declining levels of returns and, as long-term volatility increases, it is followed by increasing levels of returns (Dimitriou & Simos, 2011). The share price returns were fairly consistent between 10 October 2010 and 1 October 2015, averaging a return of 0.05 per cent. On the other hand, following President Cyril Ramaphosa’s announcement of a 21-day lockdown from 26 March to 16 April 2020, as a result of a steep increase in COVID-19 cases from 61 to more than 400 in a week, small-cap companies inevitably underwent a decline in share price returns at negative 9.17 per cent (Burke, 2020). The outbreak of COVID-19 proved to have been impactful, as the reported share price return on 23 March 2020 was the lowest return in the period under analysis. Figure 3.4 examined comparisons of the EWMA model and the HSD whereby the latter failed to realise share price volatility shocks.

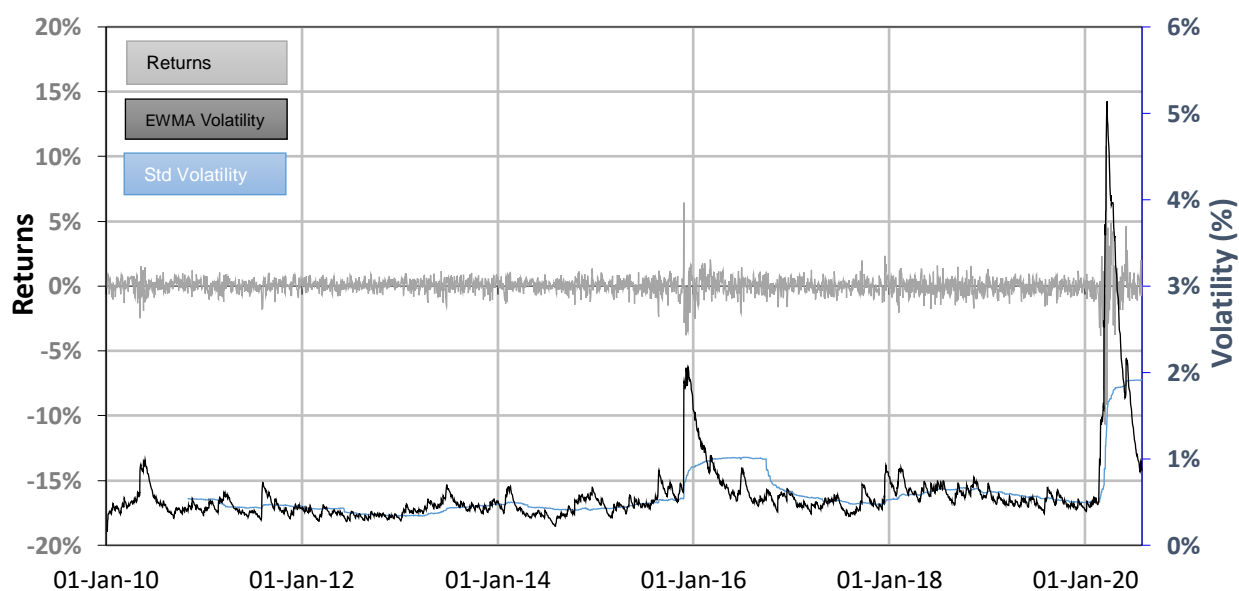


Figure 3.4: Comparison of the EWMA and the HSD for small-cap shares

Following the application of the HSD volatility of a fixed and equal weight to all observations during the sampling period it, thus, showcased a various volatility trend to that of EWMA volatility as shown in Figure 3.4. The starting sampling period of the HSD volatility period was the 1

November 2010. This was the date on which the highest share prices were reported at 12 per cent in the commencement of what was to be called the lost decade of the JSE. Moreover, in the calculation of the historical standard deviation volatility, the period of small-cap share returns before 2 November 2010 namely: 4 January 2010 to 1 November 2010, was factored in. This gave a volatility of 0.54 per cent, implying a variance in a set of small-cap share returns, in comparison to the average of the returns at negative 0,063 per cent.

As the simplest measure of volatility available, the historical standard deviation volatility remained as a drawback towards the weight of share price since all the daily share price returns were getting the same weight, following an equal-weighted approach (Larequad, 2015). Errais & Bahri (2016) argue that this is a weakness, because whenever share price shocks or spikes occur, the historical standard deviation volatility will fail to capture such shocks. There were three distinct share price shocks which occurred on 7 August 2010, 11 December 2015, and 23 March 2020, respectively, and it is evident from Figure 3.4 that only the EWMA model was able to capture these share price shocks. Not only was the model able to capture share price shocks, but it also overcame the weakness of the historical standard deviation volatility by assigning the same weight to recent and distant share price returns in the sampling period. The continuous update of forecast in volatility, subject to the availability of new information, provided a higher preference for EWMA to the HSD. It did this with a single parameter denoted as lambda (0.931).

The performance of the secondary sector was lower than that of its tertiary and primary counterparts, where a price shock was experienced on 7 August 2010. With the EWMA model of 0.84 per cent, and a share price return of negative 2.48 per cent, the secondary recorded a growth rate of negative 3.9 per cent, while the tertiary and primary sectors had growth rates of 2.0 and 24.5 per cent, respectively (StatsSA, 2010). In the primary sector, the largest contributor was the mining and quarrying industry, at 6.5 per cent. Meanwhile, a 3.4 per cent in the tertiary sector, the transport, storage and communication industry gave a 2.6 per cent increase in GDP quarter-on-quarter (StatsSA, 2010). The inverse relationship between volatility and share price return also captured on 4 August 2014, with a EWMA volatility of 0.23 per cent. This was because of the information regarding the third quarter of GDP.

The secondary sector declined by negative 2.0 per cent (StatsSA, 2014). In this sector, manufacturing experienced a decline of negative 3.4 per cent and electricity, gas and water declined by negative 1.1 per cent. The model reacted quickly, not due to the shock itself, but to the response to the growth of GDP in the fourth quarter. On 19 December 2014, primary and secondary sectors grew by 13.3 per cent and 7.2 per cent, respectively (StatsSA, 2014). Both sectors included small-cap companies with a core focus on mining, agriculture, manufacturing, construction, and

electricity. It was also important to include the tertiary sector as it contributed fairly to the economy and encompassed small-cap companies with shares traded on the JSE. Hence, StatsSA (2014) states that the tertiary sector grew by 1.8 per cent.

By using the EWMA model, the study uncovered the fact that market fluctuations had a tendency of influencing small-cap shares towards volatility. The price shock on 11 December 2015, with EWMA volatility of 1.99 per cent, illustrated small-cap shares a high level of volatility. The model thoroughly captured the high level of volatility, compared to the historical standard deviation, whereby volatility was at 0.83 per cent. The departure of the former finance minister, Nhlanhla Nene, as a result of heightened political risk, the business confidence index stood at an all-time low of 79,6 (Dludlu & Mapenzauswa, 2016). Meanwhile, the high level of volatility had not reached that of 11 December 2015 as investors with shares in small-cap companies were vigilant on which companies to construct their investments.

Apart from the abovementioned three-price shocks, all of which were driven by low-level performance in the secondary sector and political risk, another one occurred on 23 March 2020. This price shock was the biggest, as EWMA volatility was at 4.87 per cent, with share price returns declining to a low of negative 9.17 per cent. The depletion of investment portfolios, job losses, and consumer default on their credit loans were amongst major consequences of COVID-19 (Haasbroek, 2020). McKay (2020) argues that the lack of diverse income in small mining companies, which were not at par with large companies that produced commodities namely: coal, platinum, and iron ore had an upper hand of remaining active during the lockdown. Even so, small-cap mining companies and other small-cap companies' employees benefited from the Temporary Employee Relief Scheme and those that were infected by the virus at their workplaces were paid through the Workmen's Compensation Fund (Botha, 2020). These measures were taken to ensure that companies remained active and cautious, while conducting their respective daily work activities to continuously contribute to the struggling economy. Similarly, Figure 3.5 captured share price shocks by GARCH (1, 1) volatility and it was evaluated as follows:

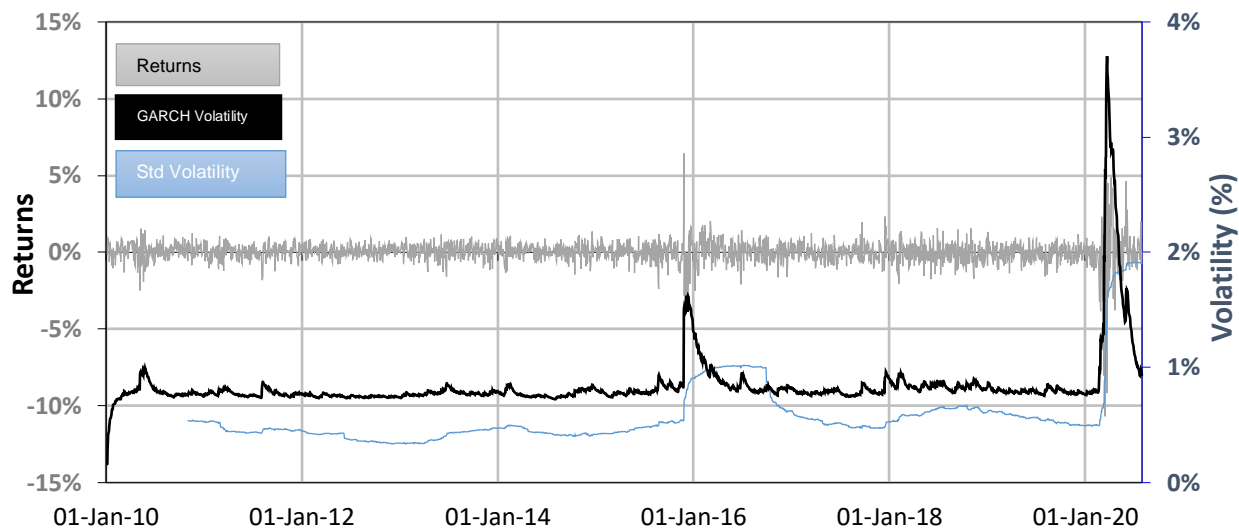


Figure 3.5: Comparison of GARCH (1, 1) and HSD for small-cap shares

The HSD volatility displays a starting sampling period of 1 November 2010, which is similar to the analysis of the EWMA volatility. The date is now synonymous with the highest share price of 12 per cent, which was recorded at the beginning of the lost decade of the JSE. The beginning calculation of the historical standard deviation volatility small-cap share return was at 0.54 per cent, which resulted in a negative percentage of 0,06 of average returns. Generalising EWMA using the GARCH (1, 1) model, whereby exponentially declining weights of share prices are analysed, implies, more weights are assigned to recent shares, while lesser weights are assigned to distant weights. This phenomenon was allowed to abide by the GARCH (1, 1) model and the next day's level of share price volatility was based on the condition of the most recent volatility (Szytar, 2010).

The GARCH (1, 1) model displayed two important features from Figure 3.5. Firstly, volatility was non-constant due to its fluctuations throughout the sampling period. This also applied to the historical standard deviation volatility. Secondly, the next day's volatility is a regressed function of today's volatility (Williams, 2011). In essence, this principle followed volatility clustering, as the GARCH (1, 1) model had moderately been constant throughout the sampling period with a few major shocks on 5 January 2010, 11 December 2015, and 23 March 2020. The share price shocks were those of the lowest volatility, moderately high volatility, and highest volatility recorded, respectively. The lowest volatility in the sampling period under the GARCH (1, 1) model was negative at 0.16 per cent.

The low volatility was a result of the 2008/09 financial crisis, which had negatively impacted all sectors of the economy. This resulted the overall GDP of 2009 recording a negative 1.5 per cent (Plecher, 2020). However, the model captured the rise in share price volatility during the period of

economic recovery as the share price volatility was at 0.98 per cent in the second quarter of 2010, as captured on 26 May 2010. The tertiary sector had a major recovery of 4.5 per cent and, meanwhile, the primary and secondary sectors contributed negative 13.2 per cent and 3.7 per cent, respectively (StatsSA, 2010). Most small-cap companies operated within the tertiary sector notably in the personal services, finance, and trade sub-sectors (Bergman, 2019). The GARCH (1, 1) model had its highest volatility on the same dates (11 December 2015 and 23 March 2020) as the EWMA model.

The moderately high volatility of the GARCH (1, 1) model was at 1.57 per cent which was less by 0.42 per cent volatility in share prices using the EWMA model. Hogg (2016) argues that the repercussions of the firing of the former finance minister, Nhlanhla Nene, and his replacement by an unknown figure, Des van Rooyen resembled a heightened political risk to the economy. Hogg (2016) further elaborated that losses stemmed from the sale of South African bonds, and sensitive rand currency with interest-rate sensitive shares was at 500 billion rand which was within two days of Des van Rooyen’s appointment as the new finance minister. On the other hand, the highest volatility of the GARCH (1, 1) model, as captured during the COVID-19 extreme event was at 3.51 per cent, which was less by 1.36 per cent volatility in share prices, when using the EWMA model. Extreme events COVID-19, and the 2008/09 financial crisis, unlike the heightened political risk, which did not fit in the category of an extreme event, had a commonality in the form of leaving behind traces of an unstable economy. Figure 3.6 examined such events in detail.



Figure 3.6: Extreme events for small-cap shares

The extreme value is based on the theory that within a probability distribution, an extreme value is the probability of events that are more extreme in comparison to previously observed events

(Odening & Hinrichs, 2002). These events have a low probability of occurring, however, when they do, they contribute a significant part towards the destruction of the economy (Trapin, 2016). As such, they leave behind a trail of a destabilised economy, that will either take a long period to recover or may not be as functional as it was before any of these events. From 2007 to 2020, the small-cap shares displayed three instances, whereby the companies in this category were hard-hit. Firstly, the 2007/08 financial crisis was concentrated in the financial sector, where the South African economy declined by 1.5 per cent (Maeko & Mathe, 2020). Small-cap shares declined from 372 rand on 31 October 2007 to 197 rand on 10 March 2009. Secondly, following the ousting of the former finance minister, Mr Nhlanhla Nene, the rand declined to a record low against the dollar. Oyedele (2015) deduces that the rand declined by three per cent to as low as 15.0563 rand against the dollar. Small-cap shares declined from 624 rand on 20 May 2015 to 483 rand on 21 January 2016. Lastly, the COVID-19 pandemic is still causing financial stress in all sectors as the lockdown costs the South African economy an estimated 13 billion rand a day (Madhi et al., 2020).

Value at Risk denoted as VaR is a measure of market risk, that measures the worst loss that might be expected from holding security over a while, with a certain probability (Fernandez, 2003). VaR is used for internal risk control, taking into account a 95 per cent confidence level. Meanwhile, the likely behaviour of abnormal large share price losses is quantified using the extreme value theory (Singh *et al.*, 2011). Extreme values of small-cap shares amounted to 0.97 per cent and 1.12 per cent which both accounted for the period 02 January 2007 to 31 July 2020. The difference between the two values laid in the manner in which 1.12 per cent, was determined using the standard normal distribution, and the standard deviation of a supplied set of share price returns ranked from lowest to highest. On the other hand, a 95 per cent confidence interval implied a 95 per cent certainty that the accurate extreme value was 0.97 per cent. Figures 3.3 and 3.5 were based on the volatility of small-cap shares using the EWMA and GARCH (1, 1) models. They illustrated a pattern in these unlikely extreme events, financial risks and the negative relationship between volatility and share price returns.

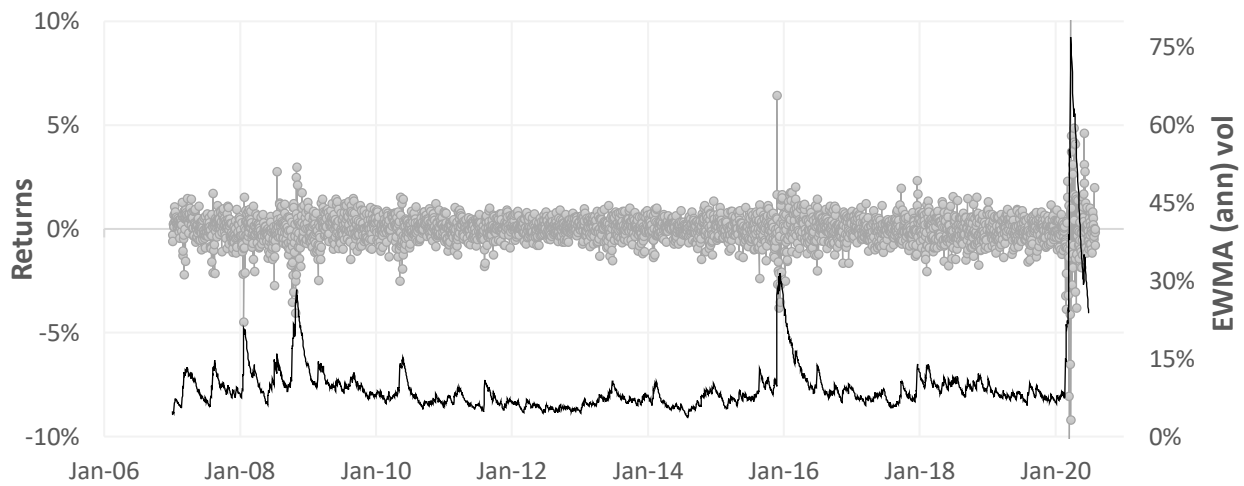


Figure 3.7: Extreme values using EWMA model for small-cap shares

The EWMA daily volatility was annualised as there are 250 trading days annually. The period 2 January 2007 to 31 July 2020 was chosen to emphasise the extreme value theory. Meanwhile, the share price return throughout the depicted period averaged negative 0.13 per cent. The small-cap share prices and the share price returns in the aforementioned three extreme events shared a similar trait. During the financial crisis of 2008/09, the share price declined to 196 rand with a share price return of negative 0.85 per cent on 10 March 2009, from a high of 373 rand with a share price return of 0.29 per cent on 7 November 2007. On the other hand, the outbreak of COVID-19 occurred in South Africa on 5 March 2020 when a citizen who had recently returned from a trip in Italy was diagnosed with the virus. When the news was made public, it caused investor panic and raised an alarm among the citizens who feared that there would be widespread infections (Mkhize, 2020). Uncertainty in the small-cap financial markets led the share price to return at negative 9.17 per cent on 23 March 2020. This followed the president’s announcement of a 21-day lockdown that was intended to curb the spread of the virus. On the day of the announcement, there were more than 400 cases (Kiewit *et al.*, 2020). The lockdown took effect from midnight on 26 March 2020 to 16 April 2020, as illustrated in Figure 3.8 (Burke, 2020). The EWMA model volatility reacted in the opposing view of the share price and share price return movement, due to the negative relation between share price return and volatility which was discussed in Figure 3.3. The annualised volatilities on 30 October 2008, 11 December 2015, and 23 March 2020 were at 28.3 per cent, 31.4 per cent, and 77 per cent, respectively, when factoring 250 trading days in a year.

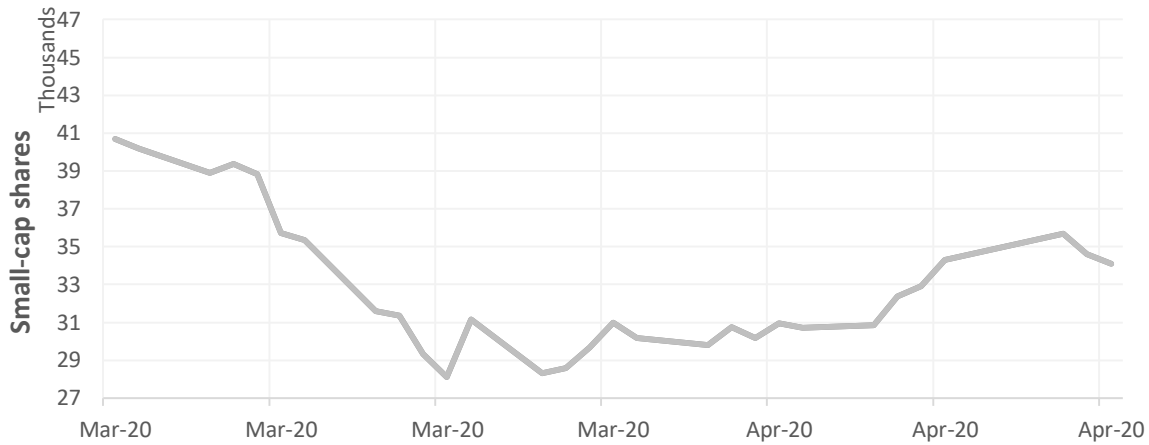


Figure 3.8: Small-cap share movement during the 21-day lockdown in South Africa

Before the announcement of the 21-day lockdown, following the first case of COVID-19 that was reported on 5 March 2020, on the same day (5 March 2020) share prices had declined from 407 rand to 281 rand on 19 March 2020, which was the lowest share price in the period under analysis. The decline was as a result of the global unrest caused by the rising cases of the virus and the declaration by the World Health Organisation that COVID-19 was a pandemic (World Health Organisation, 2020). After the announcement of the lockdown, share prices averaged 312 rand from 23 March 2020 to the end of the 21-day lockdown on 16 April 2020. In the days leading up to the official commencement of the lockdown, agitated consumers rushed to supermarkets, resulting in the panic buying of essential items (Koko, 2020). Equally so, a 30 per cent decline in global equity markets whereby the FTSE/JSE All Share Index was down by 27 per cent led to investor panic (Lapping, 2020).

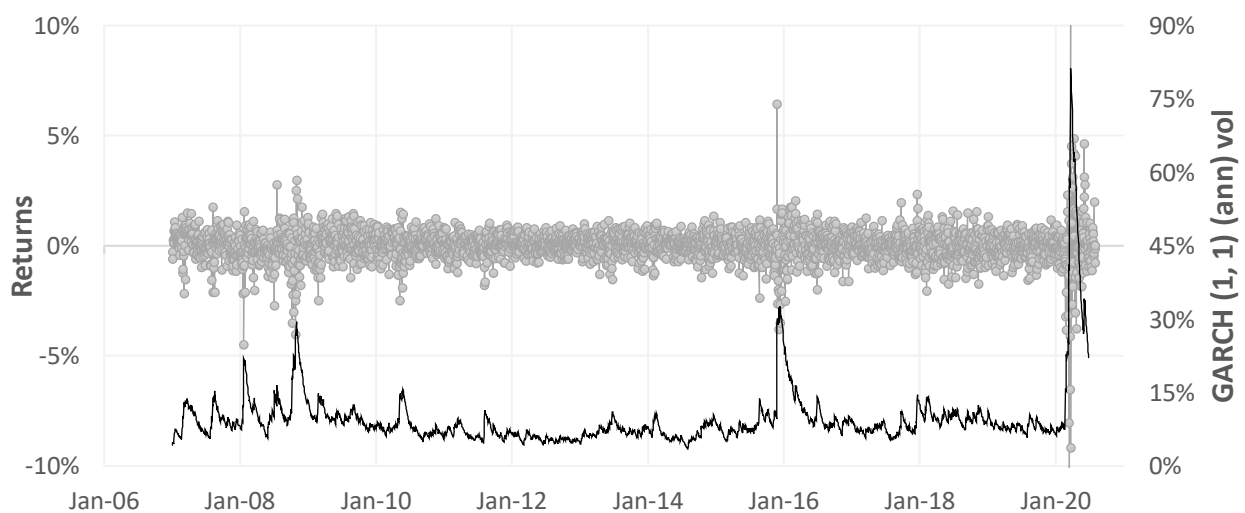


Figure 3.9: Extreme Values using GARCH (1, 1) for small-cap shares

The GARCH (1, 1) model daily volatility was annualised since there are 250 trading days each year. Both the EWMA and GARCH (1, 1) models made use of the same small-cap share price in the period from 2 January 2007 to 31 July 2020. The average of the share price throughout the period was negative at 0.13 per cent. Similarly, the GARCH (1, 1) model volatility reacted contrary to the share price return movement. The annualised volatility on the following dates, 30 October 2008, 11 December 2015, and 23 March 2020 was at 22.9 per cent, 24.9 per cent, and 55.6 per cent respectively. The stated annualised volatilities were influenced by the weighting components that made up the model. The three weightings were still applicable and contributed a distinction with the EWMA model. Beta constituted the value of 0.931. By adjusting 0.931, the weighting was not equal to one as gamma and alpha remained at constants of 0.0345.

At this point, an inverse relationship between volatility and small-cap share price returns had been reported, as illustrated in Figures 3.3, 3.4, 3.5, 3.7 and 3.9. The end of the sampling period, being 31 July 2020, is of importance in determining the optimal lambda at that date for a sample of small-cap shares, given the extreme COVID-19 event and the impact it had on the optimal lambda itself. This was followed by a one-day volatility forecast at 0.51 and 0.79 using EWMA and GARCH (1, 1), respectively.

3.5 CONCLUSION

The study aimed to represent which model, between EWMA and GARCH (1, 1), was more preferable in forecasting volatility in small-cap shares, using the small-cap index (J202), provided by the JSE. In addition, the study sought to determine the optimal lambda at the end of the reporting period. In the period of analysis, 01 January 2010 to 31 July 2020, the EWMA model factored in an important element, a decay factor for daily data at 0.931.

Firstly, the decay factor for daily data at 0.931 indicated its relevance to the model as share price weights got adjusted when an adjustment was applied. When decreasing the value 0.931, share price returns that dated to an earlier period received less weight, while those at dates that were approaching the latest i.e. 31 July 2020, received more weight. A similar approach was applied to reducing the value of 0.931. The inclusion of this value, was not only at the forefront of affecting the adjustment of share price return weights, but most importantly, whenever it was adjusted, the volatility graph was also affected. However, it should be noted that in the models' impact by the value, the characteristic of small-cap shares being more volatile was abided to. Moreover,

irrespective of the adjustment of 0.931, the EWMA model captured an event that was extreme, thereby posing large risks for investors in the index.

Secondly, the GARCH (1, 1) model had an important feature, persistence, implying that the model applied three weights namely: gamma, alpha, and beta, in constructing the volatility of small-cap share prices, thus, the model's long-run variance meant a quick reversion to the mean. The model readjusted quicker after the share price shock during the extreme events recorded in the period. If the long-run variance had a value closer to one, then the model would have captured share price shocks at a slower rate. A low persistence was more preferred than a high persistence (which would have led to no mean reversion). This quick readjustment was well illustrated after the volatility drastically increased on 7 August 2010, which was characterised by poor performance in the secondary sector of the economy; 11 December 2015, which witnessed heightened political risk; and 23 March 2020, when the announcement of a 21-day lockdown as a result of an outbreak of COVID-19 was made. Both volatilities indicated a relationship between share price return and volatility. On that basis, low volatility implied high share price return. However, an analysis based solely on that relationship is not conclusive, therefore, the GARCH (1, 1) model would have been preferred. Yet, there were instances when the EWMA model volatility was low and the share price return was high.

Thirdly, the study would have been incomplete without the inclusion of the HSD, as it remained at the core of the analysis. The HSD, as a measure of risk during the share price shock, had high volatility, which implied that the higher the standard deviation, the riskier the investment in small-cap shares. It did not track a similar movement of volatility as the two models did. This variation was based on the fact that both models took the optimal lambda into account, as it was used as a smoothing parameter. Despite this, the measure of risk was embedded in the analysis of market volatility, as the risk in the premise of investing was not viewed negatively as the riskier a security was, the greater potential it had for expected financial returns. Furthermore, the calculated optimal lambda indicated the higher weighting applied to the present day's share price returns and lower weighting to share price returns which dated earlier in the reporting period, while a notable instability in the market which led to high volatility, as indicated in the outbreak and impact of COVID-19.

Finally, the decision on which model was preferable was based on an individual investor's preference as both models have shown that they track relatively similar volatility of share price returns and whenever there was an extreme event – like a financial crisis or COVID-19, they thoroughly captured and recorded such events. Moreover, it was advisable to make use of both

models in order to simultaneously allow a broader view of share price return volatility forecast when considering investing in small-cap shares.

3.6 RECOMMENDATIONS

As the study was focused mainly on forecasting volatility after day n-1, it is recommended that more emphasis could be put on forecasting volatility and determining the optimal lambda using monthly data and the mispricing of small-cap shares amid COVID-19 pandemic.

3.7 LIMITATIONS

The limitation of volatility forecasting was based on the models' calculations with a minor influence of the macroeconomic factors which play significant roles in fundamental analysis.

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CHAPTER 4: RESEARCH ARTICLE 2

ANALYSING VOLATILITY DURING EXTREME MARKET EVENTS USING THE MID CAP SHARE INDEX

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ABSTRACT

The underperformance of the JSE from 2010 to 2019, as a consequence of the collapse in mid-cap share investments signified the high risk of investing in mid-cap companies. The outbreak of COVID-19 affected the optimal lambda and mid-cap share price returns during the analysis period, that was extended to 31 July 2020. For this purpose, the objective of the study is to forecast volatility at the end of day $n-1$ applying the EWMA and GARCH (1, 1) models using the mid-cap share index (J201). Furthermore, the study aims to calculate the optimal lambda during an extreme event, in this instance the COVID-19 global pandemic. The models examined the negative relationship between share price returns and volatility during the COVID-19 extreme event which led to a fat-tailed distribution of returns in share price returns. During the month of December 2015, Fitch Ratings assigned an unfavourable negative BBB credit grade to South African investment grade, and in the days following the COVID-19 lockdown, share price returns plunged, consequently encouraging panic selling by risk-averse investors.

JEL: G01, G11, G17

4.1 INTRODUCTION

Middle capitalisation (mid-cap) shares, similar to small capitalisation (small-cap) shares, generate their earnings within the boundaries of South Africa. Mid-cap shares, however, fall outside of the 40 largest shares listed on the JSE. Mid-cap shares are made up of the 60 companies that are tracked in the mid-cap share index (J201). Following the 2008 financial crisis, these shares gained momentum from investors for inclusion in an investment portfolio (Ashburton Investments, 2020). During the period of the financial crisis, their performance was more favourable, in comparison to the small and large-cap shares (le Roux, 2018). Mid-cap shares were at negative 17.81 per cent, and, meanwhile, small and large-cap shares were at negative 33.87 per cent and negative 28.25 per cent respectively. Mid-cap share positioning in the JSE all-share index consists of an ability to characterise small and large-cap shares while their overall risk of share investment is lower than the small-cap shares (Jackson & Schmidt, 2020). However, even with the popularity of large-cap shares, the level of stability in returns for investors, reflecting 80 per cent of the total market capitalisation of all JSE listed companies, risk-averse investors are still inclined to invest in large-cap shares and keep away from mid-cap shares (Rizal *et al.*, 2018).

Furthermore, after each economic downturn, mid-cap shares tend to recover much slower than small-cap shares (Hulbert, 2020). Nonetheless, this does not discount share investments made within the mid-cap sector, as previously underperforming large-cap companies delisted from the large-cap index J200 to the mid-cap index J201, continuously have a high-quality management team that provides investors an opportunity to identify undervalued liquid shares that are incorrectly priced by the market (Klein, 2019; Doukas *et al.*, 2010). It becomes manageable to sell shares before a market downturn. Montag & Caldwell (2020) showcased that in the period under analysis, mid-cap companies were safer to invest in because they fall between the volatile small-cap shares and large-cap share stability, thus, assuring long-term growth. The value of mid-cap share increases with time, thereby investors gain higher share price returns when compared to small and large-cap shares, which proved to be the case during the 2008 financial crisis (Angerame & Deutsch, 2015). However, mid-cap shares are often overlooked because of less analysis coverage which, in turn, becomes a proponent for the continuous uncovering of undervalued shares, since they offer small-cap growth that is aligned with large-cap stability.

Less analysis coverage provides an opportunity to forecast the volatility of mid-cap share price returns using the EWMA and the GARCH (1, 1) models. Such forecast will convince active and potential risk-averse investors to invest in mid-cap shares and comprehend volatile share price movement amid any market downturn. In addition, the use of fundamental analysis should be prioritised in providing analysis on the impact of the underperforming South African economy on mid-cap companies (Cotterill, 2020). There is also a need to calculate the optimal lambda that is affected by extreme events for the specified period, as identified in the respective models. To analyse daily share prices from 1 January 2010 to 31 July 2020, considering the extreme events that occurred during the period named the lost decade of the JSE, and the duration of the COVID-19 global pandemic. Therefore, the objective of the study is to examine and forecast mid-cap share volatility during extreme events, using the EWMA and GARCH (1, 1) models to forecast the volatility of the mid-cap share index (J201).

4.2 LITERATURE REVIEW

The mid-cap index is made up of shares that are ranked 41 to 100 on the JSE; they are medium cap shares because of their market capitalisation range. Klein (2019) states that mid-cap shares consist of market capitalisation that is between 1 billion and 10 billion rand. Whereas small-cap and large-cap shares consist of market capitalisations that are below 1 billion and over 10 billion rand, respectively (JSE, 2020). The mid-cap index is a representative of 85 per cent to 96 per cent of the full market cap value of all qualified ordinary securities listed on the main board of the JSE (JSE,

2020). To raise capital, mid-cap companies sell shares, instead of taking debt so that they continuously grow, while also attracting potential investors (Kim & Weisbach, 2005).

In conducting market research, potential and active investors will find important features that make up mid-cap shares. These shares are diverse, as they are characterised by companies that offer long term stability and those that would have recently moved from the small-cap category, thus allowing greater returns (Reeves, 2020). Comparing to small-cap shares, mid-cap shares have the ability to become less volatile while remaining more volatile to large-cap shares during market contraction. They also have innate liquidity, which allows moderately easier transaction during the sale of shares at fair prices, a feature which an investor should be aware of (Amadeo, 2020). Mid-cap shares might not be as exciting as small-cap shares that have recently received their initial public offering (IPO). However, they have been thoroughly researched as much as their counterparts in the large-cap shares category. As such, mid-cap shares are not as risky as their small-cap counterparts, because during an economic downturn they are less likely to go bankrupt. Their credibility of being active in the stock market for a long period assures them of stability (Wisdomtree, 2018).

Mid-cap companies attract potential and active investors, as they are positioned in the border and exploit both ends of small and large-cap shares. They find themselves in a less volatile path as they would have proved to their stability by moving past the riskier shares in small-cap companies and gearing towards long term growth (Kumar & Misra, 2015). For that reason, investors will benefit from several advantages. Provided that they are positioned as mid-cap shares, they allow for stock appreciation, whereby asset values increase over time, due to increased demand, reduced supply of assets, and change in inflation, and interest rates (Pástor & Pietro, 2003). Kennon (2020) points out that mid-cap companies make provision for substantial dividends in instances where the company is performing well and profits are shared or whenever there is no major project expansion as a result of a decline in share prices. During their early days of having moved from the small-cap index to the mid-cap index, there are instances in which they are overlooked because of limited attention from large institutions. This leads to low pricing, thus, allowing investors to include these shares in their investment portfolios (Muller, 2019). Despite this, mid-cap companies have an established management team that overlooks the decision-making process aimed at financial stability, while providing an examination on their financial health and history. This allows for a much constructive analysis of their ability to withstand economic downturns, such as the financial crisis of 2008/09 and the COVID-19 pandemic (Vovchenko *et al.*, 2017). In the interest of having a balanced understanding of mid-cap shares, it is important to keep in mind that these companies are not immune to the disadvantages that are outlined in the next paragraph.

Low ranking mid-cap companies, (those that are nearing the 100th rank on the JSE) are vulnerable to value trap. This implies a share price that appears to be low priced, due to trading at low valuation metrics (Penman & Reggiani, 2014). Such an occurrence attracts potential investors that are on the lookout for low priced shares of companies that perform better than those of industry competitors. However, whenever the share price continues to decline significantly, it poses a threat to investors that would have already bought into the mid-cap companies. In this instance, the investors find themselves trapped in a company that yields low profits and operates on limited cash flow (Biery, 2017). When comparing mid-cap and small-cap companies, it is evident that with mid-cap shares operating on the scale of value appreciation and high profits (profits larger than small-cap shares), insufficient resources and business models that allow them to remain as mid-cap indefinitely pose a threat. This is problematic because small-cap companies moving up the ranks and experiencing exponential growth with increasing market capitalisation will see such stagnant mid-cap companies moving down the rankings and label them as the next small-cap companies (Martin, 2019). Likewise, they are also prone to financial bubbles, which pressurises such companies to shift from the mid-cap index to the small-cap index. Nevertheless, Figure 4.1 illustrates the mid-cap and long cap shares during the period 2007 to 2009 whereas the concept of a recession and recovery was captured.



Figure 4.1: Behaviour of mid-cap share prices against the Top 40 companies during recessions and recoveries

Source: IRESS INET BFA (2020)

Figure 4.1 shows the performance of the share prices of the JSE Top 40 and mid-cap companies. During the period 23 May 2007 to 27 October 2008, mid-cap shares were at 372.28 and 216.81 rand respectively. Mid-cap shares experienced a negative percentage change of 41.76 per cent. In the same period, JSE Top 40 shares were at 260.79 and 166.70 rand respectively. The JSE Top 40 shares also encountered a negative percentage change of 36.08 per cent. During the period outlined, both mid-cap and JSE Top 40 shares underwent a significant decline in share prices. Moreover, the JSE Top 40 share had the highest share price on 26 May 2008, at 308.01 rand. Meanwhile, the highest recorded mid-cap share price was captured on 23 May 2007. Likewise, more investors bought rather than sold shares and this caused a rise in share prices. While mid-cap shares resemble qualities of small and large-cap shares, their rise in a recovery phase does not occur at a quick rate as the small-cap shares, irrespective of a larger decrease during a recession. Nonetheless, mid-cap shares still reflect attractive value appreciation. Similarly, the performance of both small and large-cap shares grows during the expansion phase of the business cycle. Quarterly GDP growth in the second and fourth quarter in 2007 was at 0.8 and 1.4 per cent, respectively (Country Economy, 2007). In the case of mid-cap companies, capital is inexpensive and this places the management team in a position to invest in capital equipment, or perhaps they could focus on merging with another company that shares similar values and acquire start-ups that indicate potential growth (Amadeo, 2020). The types of investors likely to buy into mid-cap shares are seasonal, and these are discussed below.

Seasonal investors are inclined to invest in mid-cap shares given their position of being exposed to both ends of risk moderation and substantial returns. Chang *et al* (2017) define a seasonal investor as an individual that narrows focus on volatile markets while holding the view of the uncertainty as an important element in the long-term. Mid-cap companies that do not seek to grow and move from the mid-cap index to the large-cap index might discourage a seasonal investor. Seasonal investing is effective when used with fundamental and technical analysis. However, timing the market can be a disadvantage when not used effectively, as it is key to maximum profits (Kulp, 2019). Seasonal investors can be discouraged by time consumed on thoroughly staying updated on the latest trends. Nevertheless, these types of investors are driven by easily available data, as the historical trends and performance of shares are tracked from the past. This gives an overview of the seasonal cycles, which the investor can use for future predictions on the probable period for investing. The principle of buying low and selling high applies in this case. Buying mid-cap shares at the commencement of the trend and selling them by the end period of the trend at higher share prices is common for reaching maximum profits (Shim, 2000).

4.3 METHODOLOGY

IRESS INET (Pty) Ltd is an online tool for obtaining financial data that are used for analysis. The period under analysis is from 01 January 2010 to 31 July 2020. It should be noted that the lost decade of the JSE spans from 01 January 2010 to 31 December 2019. Extending the study period to 31 July 2020 is of importance since it accommodates the aspect of the extreme value theory and the impact of COVID-19 in finding the optimal lambda, as at the end of the study period (31 July 2020) of mid-cap shares. The starting date 01 January 2010 was chosen on the basis of the share prices of mid-cap companies which underwent a steep decline. Meanwhile, on 31 December 2019, shares were trading at negative four per cent. Daily returns are determined using daily data on the aspect of information that stems from low-frequency trends in volatility, specifically in a crisis (Danielsson *et al.*, 2018). The EWMA and GARCH (1, 1) models are appropriate for daily data, as they make provision for the accurate forecast of the volatility after day n-1 (Guo, 2012).

The methodology is subjected to historical daily data and in using the aforementioned two models, which are derived as follows.

4.3.1 FORECASTING VOLATILITY

The EWMA and GARCH (1, 1) models emerged as the study proceeded and both were selected since they were associated with solutions provided to research questions, drawing special attention to volatility and optimal lambda as of 31 July 2020, and in the attainment of empirical objectives for the study. The section was broken down into the EWMA and GARCH (1, 1) models.

The symbol σ_n was the volatility of a share price on day n, which was forecasted on day n-1. The variance was of the symbol σ_n^2 which was referred to as the square of the volatility. Meanwhile, historical data was forecasted as follows:

Share value at the end of day i was S_i . The variable u_i was the continuous compound return between the end of day $i - 1$ and the end of day i which provided the following equation:

$$u_i = \ln\left(\frac{S_i}{S_{i-1}}\right)$$

The variance σ_n^2 which used the most recent m observation on the u_i to have a fair estimate of the variance per day was supplied with this equation:

$$\sigma_n^2 = \frac{1}{m-1} \sum_{i=1}^m (u_{n-i} - \bar{u})^2 \quad (4.1)$$

Whereby \bar{u} implied the mean of the u_i 's:

$$\bar{u} = \frac{1}{m} \sum_{i=1}^m u_{n-i}$$

The above formula \bar{u} was modified based on the study analysis using daily volatility and it took the following form:

- u_i was the percentage change in the share price between end of day $i - 1$ and day i , which allows

$$u_i = \frac{S_i - S_{i-1}}{S_{i-1}} \quad (4.2)$$

- The symbol \bar{u} was zero, shown as a presumption.
- The symbol m replaced $m - 1$.

The variance (square of the volatility) took the following form:

$$\sigma_n^2 = \frac{1}{m} \sum_{i=1}^m u_{n-i}^2 \quad (4.3)$$

Whereby u_i was provided in (4.2).

4.3.2 WEIGHTING SCHEMES

As the above equation represented equal weight given to the m observations, the current level of volatility (σ_n) was a significant feature in forecasting and more weight was focused on recent data.

In accordance, the weighting scheme took the following form

$$\sigma_n^2 = \frac{1}{m} \sum_{i=1}^m \alpha_i u_{n-i}^2 \quad (4.4)$$

The variable α_i was defined as the amount of weight provided to the observation i in the preceding days. The value of α , which stands for the weights, is positive (Nilakantan & Mistry, 2013). A long-run variance (V_L) and its weight (γ) was assigned and in which transformed the model to a new form which was as follows

$$\sigma_n^2 = \gamma V_L + \sum_{i=1}^m \alpha_i u_{n-1}^2 \quad (4.5)$$

The above formula was an ARCH (m) model. The forecast of the variance was on the basis of a long-run average variance and m observations. The long-run variance and its weight (ω), about the above equation, were modified as

$$\sigma_n^2 = \omega + \sum_{i=1}^m \alpha_i u_{n-1}^2 \quad (4.6)$$

Following equation (4.4) and (4.6), various approaches were implemented to track volatility. These approaches are EWMA and GARCH (1, 1) models.

The EWMA model was shown in equation (4.4), whereby weights α_i declined exponentially when moving back in time. In particular, α_{i+1} was defined as $\lambda\alpha_i$ whereby λ was a constant between zero and one. Such a weighting scheme was simplified with a formula for volatility forecasting, which is as follows:

$$\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1 - \lambda)u_{n-1}^2 \quad (4.7)$$

The forecast of the volatility (σ_n) of a variable for day n was calculated from σ_{n-1} and u_{n-1} .

Adeyuyi (2016) points out that the EWMA model was made to follow changes within volatility. A huge move within the market variable on day $n-1$, and u_{n-1}^2 , as shown in equation (4.7) caused the volatility forecast to progress upward. Meanwhile, lambda was responsible for the responsiveness of daily volatility forecast and was subjected to the leading percentage change (Finance Train, 2020). A higher weight was also provided to u_{n-1}^2 and, when volatility was determined, the value of λ declined. Meanwhile, as λ approached 1.0, the value increased in a way that the forecast of daily volatility reacted fairly slower to data that were provided by daily percentage change.

The value of the optimal lambda had to be calculated. On the other hand, concerning the GARCH (1, 1) model, the variance (σ_i^2) was fundamentally calculated from the following: the long-run variance (V_L), σ_{n-1} and u_{n-1} . The formula for volatility forecasting concerning the GARCH (1, 1) model was as follows:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (4.8)$$

The equation $\gamma + \alpha + \beta = 1$ signified the unity of the weights in which the symbol γ pointed to the weight assigned to V_L , whereas, α was the weight assigned to u_{n-1}^2 and β was the weight that was assigned to σ_{n-1}^2 .

On the other hand, the EWMA model weights were as follows: $\gamma = 0$, $\alpha = 1 - \lambda$, and $\beta = \lambda$. As the variance (σ_i^2) was based on current observations of u^2 and most recent forecast of the variance rate, the (1, 1) in the GARCH model was determined. The weight provided to V_L was also written as ω . Hence, the GARCH (1, 1) model was rewritten as follows:

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (4.9)$$

The variation between the two models was based on the premise of the GARCH (1, 1) model allocating weights towards the long-run variance volatility and from the analysis, the more preferable model was determined.

4.4 RESULTS AND DISCUSSION

The objective of the study was to analyse the optimal lambda factored in the calculation of the EWMA and GARCH (1, 1) model's forecasting after day $n - 1$. While investments in small-cap shares were of fast-growing companies under the equities asset class, they were deemed favourable for their potential of being undervalued and outperforming the market during the recovery from COVID-19. Meanwhile, mid-cap shares were also favoured for their positioning. Mid-cap shares were regarded as less-volatile, compared to small-cap shares. Moreover, they reflected more growth potential than large-cap shares. The EWMA and GARCH (1, 1) models were set up against the historical standard deviation. The historical standard deviation was applied to identify its weakness in mid-cap shares, whereby similar share price return weights were tracked in the lost decade of the JSE and the first seven months of the year 2020, when the series of COVID-19 lockdowns were in full operation.

In agreement with the theoretical objective that puts forward the importance of volatility forecasting of share price returns in mid-cap shares and its drawbacks namely: the inability to recover at a quick rate from large shocks, as depicted on the EWMA model. However, this seeming drawback was a benefit for the GARCH (1, 1) model, which normally readjusted at a quick rate to the effects of the shocks that the JSE underwent. The identified extreme events were discussed in a broader rather than a limited sense. The broader sense held that the models played a significant role in the share investment construction made by active and potential investors. On the other hand, the limited view only took into account the historical standard deviation, which was explored for

its major drawback, as discussed above. Table 4.1 and Figures 4.3 to 4.9 are in alignment with the empirical objectives of chapter 1 which, among others, indicated whether COVID-19 could be categorised as an extreme event. In addition, the exploration of the relationship between the EWMA and GARCH (1, 1) models using daily data was conducted. Furthermore, a sample of ten companies, which are categorised as mid-caps and used in the mid-cap index (J201), was selected for calculating the optimal lambda which was utilised in all the figures, where necessary. These companies were as follows: Adcock Ingram Holdings Ltd, Cashbuild Ltd, Clientele Ltd, Famous Brands Ltd, Imperial Logistics Ltd, Kap Industrial Ltd, Massmart Holdings Ltd, Murray and Robert Ltd, Oceana Group Ltd, and Sun International Ltd.

Table 4.1: Optimal lambda for mid-cap shares

Small-cap companies	Adcock Ingram Holdings Ltd	Cashbuild Ltd	Clientele Ltd	Famous Brands Ltd	Imperial Logistics Ltd	Kap Industrial Ltd	Massmart Holdings Ltd	Murray & Roberts Holdings Ltd	Oceana Group Ltd	Sun International Ltd
Phi	27.34%	5.65%	0.73%	6.72%	12.30%	0.34%	8.89%	3.21%	3.68%	31.16%
Lambda	0.996	0.978	0.949	0.896	0.923	0.979	0.970	0.970	0.918	0.999
Optimal lambda	0.974									

Table 4.1 illustrated the optimal lambda for mid-cap shares at 0.974 on 31 July 2020 whereby it was constructed using the individual companies' phi and lambda. The significance of the optimal lambda as a smoothing parameter for time series data was used for working out the exponentially declining share price weighting scheme of the observed sample period. Further, the value 0.974 was factored in the EWMA model and as part of the three weights included in the GARCH (1, 1) model. Figure 4.2 was made for the comparisons between the EWMA and the GARCH (1, 1) models against the mid-cap share price returns.

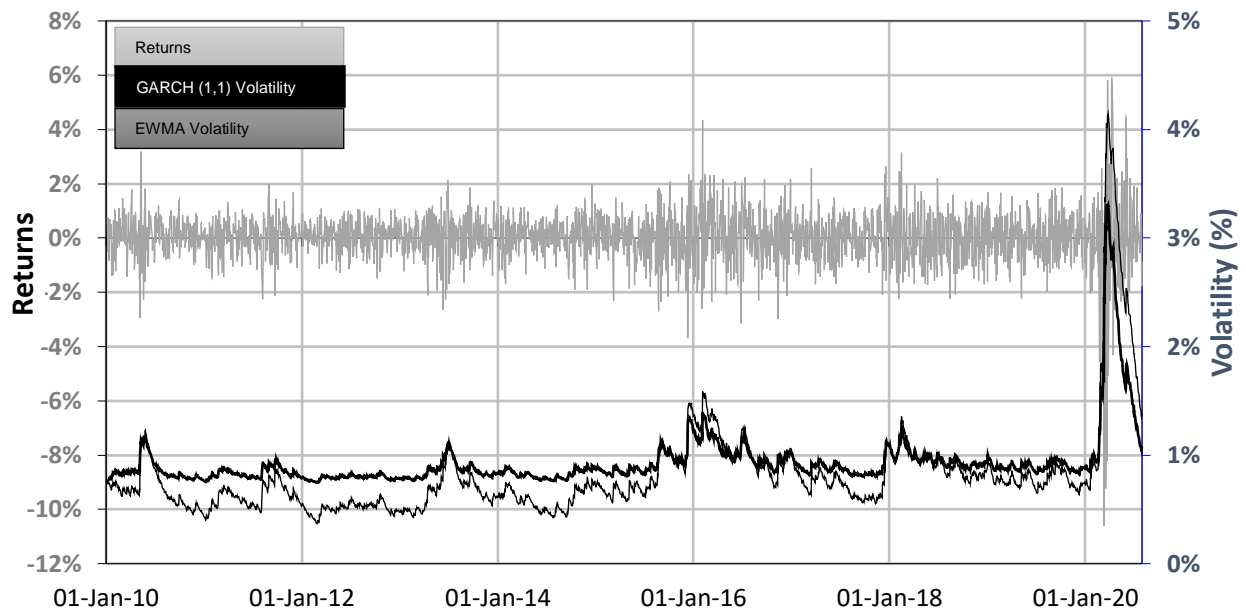


Figure 4.2: Comparison of EWMA and GARCH (1, 1) volatilities for mid-cap shares

The EWMA and the GARCH (1, 1) models displayed a relative movement of volatility, which was well captured during the periods of high and low volatility. The EWMA model factored in the optimal lambda of 0.974, whereby data were expressed in daily terms. The previous day's volatility, also referred to as the beginning period of the analysis at 4 January 2010, was taken into account together with the present-day share price return at 0.76 per cent and the optimal lambda using the equation $\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1 - \lambda)u_{n-1}^2$ to forecast volatility for 5 January 2010. This principle was abided to following the entire analysis to 31 July 2020. An exponential decline in the weights of share prices was noted in order to realise the variation from using the HSD and the presence of 0.974 was responsible for the extent of the behaviour of daily volatility forecasting and daily percentage change.

When 0.974 was adjusted to arrive at the value of zero, the weight on recent share price returns increased and, meanwhile, the weight on distant share price returns decreased. When 0.974 was adjusted to arrive at the value of one, recent share price return weights declined and those that were distant grew. Furthermore, any adjustment of 0.974, the share price return weights always added up to 100 per cent, with an exception of 0.974 adjustments to one. In that case, all share price return weights added up to zero per cent and irrespective of the adjustment of 0.974, the volatility remained persistent at an absolute value of 0.76 per cent. The significance of the GARCH (1, 1) model was presently used to also note its disparity with the historical standard deviation and the EWMA model.

The GARCH (1, 1) model had three recognisable weights namely: beta, gamma and alpha, which all had the value of 0.013, and beta with a value of 0.974. All three weights added up to one and were included in the equation $\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$. The forecast for volatility for 5 January 2010 was at 0.76 per cent and the calculation followed a similar manner as that of the EWMA model in forecasting volatility up to 31 July 2020.

The presence of both models was important in making provision for investing in mid-cap shares. These types of shares were known to provide greater share price appreciation potential and counterbalance the conventional share portfolio, which was composed of less risk, in comparison to small-cap shares (Brink, 2020). Both models captured a short-term spike in share price volatility on 11 December 2015, whereby the share price returns dipped to negative 3.67 per cent and the EWMA and GARCH (1, 1) models' volatilities were at their highest for the first time since 4 January 2010 at 1.13 per cent and 1.25 per cent, respectively. Meanwhile, the share price returns were at their lowest since the beginning of the reporting period. An inverse relationship between share price returns and volatility was in display on that date and other periods when extreme events took place. Figure 4.3 shows the variations between the EWMA and the HSD models in which the HSD model was not capturing shocks in share price volatility.

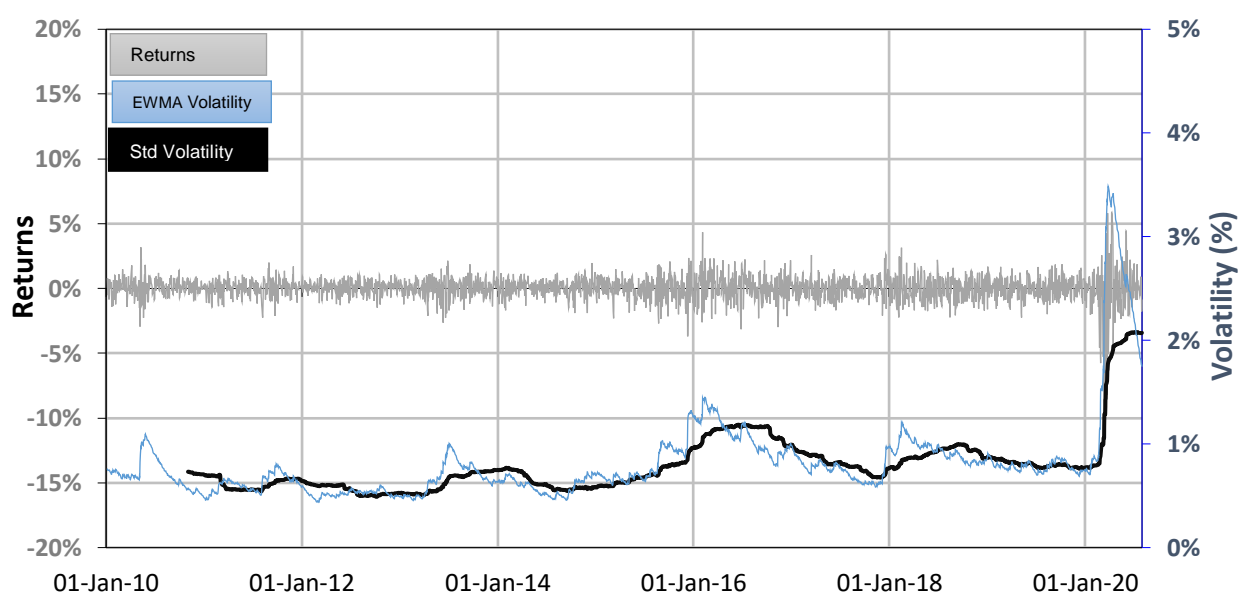


Figure 4.3: Variations of EWMA and HSD for mid-cap shares

Figure 4.3 shows a different volatility trend between the HSD and the EWMA model. The starting date for the HSD, 1 November 2010, was chosen because of the lost decade of the JSE's largest share price recorded at 12 per cent and its calculation was captured from 4 January 2010 to 1 November 2010. As a result, a volatility of 0.73 per cent was calculated, which meant a variance in a set of mid-cap share returns, when compared to the average of the returns at 0.102 per cent.

Four distinct share price spikes were encountered on 20 May 2010, 06 May 2015, 11 December 2015, and 23 March 2020.

The EWMA model was able to capture these share price spikes in volatility, in which share price returns were at their lowest. Although a steep decline in share price returns was influenced by market volatility, mid-cap companies that could not meet their profit estimates faced declining revenues due to competitive pressures. Haasbroek (2020) provides an example of one of the mid-cap companies, Spur Corporation Limited. As a restaurant company, Spur Corporation Limited suffered from the effects of the COVID-19 pandemic as its share price was 17.80 rand on 15 April 2020, a decline of 33.3 per cent from 02 January 2020. On 20 May 2010, the share price return was negative 2.27 per cent and a volatility of 1.04 per cent. This was further influenced by the slow recovery of the South African economy from the 2008/09 financial crisis. (Steytler & Powell, 2010). A negative relationship between share price returns and volatility was determined on 06 May 2015, whereby the EWMA model volatility was at 0.68, while the share price return was at negative 1.84 per cent. Meanwhile, on 11 December 2015, share price returns were at negative 3.67 per cent. The increase in mid-cap share volatility at 1.25 per cent was influenced by an adverse credit rating by Fitch Ratings. As a credit rating agency, Fitch Ratings is responsible for providing ratings towards the application of investments relative to the probability of default (Teixeira, 2020).

Fitch Ratings downgraded South Africa's Long-Term Issuer Default Credit Ratings from BB to BB- on 20 November 2020 (Fitch Ratings, 2020). The South African Reserve Bank (2017) pointed out that the downgrade was influenced by a slow economy, as the real growth rate was at 1.3 per cent, whereas in 2014 and 2013 the real growth rate was at 1.5 and 2.2 per cent respectively. On the other hand, after 23 March 2020, the South African President Cyril Ramaphosa announced the official 21-day lockdown. The national lockdown was meant to curb the spread of the COVID-19 global pandemic. The mid-cap share price returns declined to their lowest in the period under analysis at negative 8.23 per cent, while the volatility was at its highest at 3.35 per cent. The South African Reserve Bank (SARB) estimated that the 21-day lockdown would have a direct impact on the contraction of the economy at 2.6 per cent (Cronje & Omarjee, 2020).

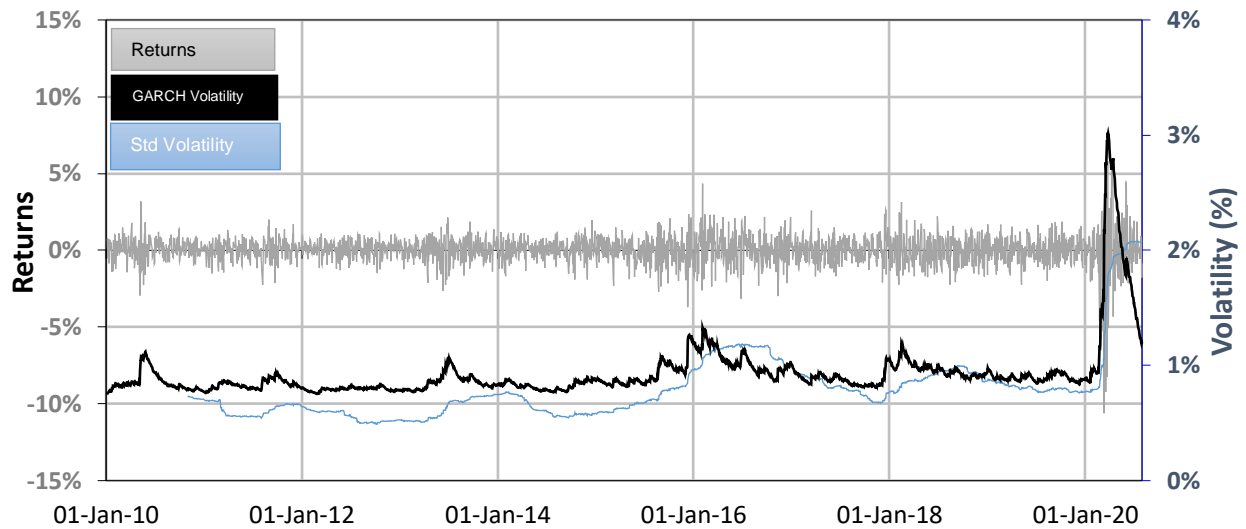


Figure 4.4: Variations of GARCH (1, 1) and HSD for mid-cap shares

Figure 4.4 illustrates a various volatility trend between the GARCH (1, 1) model and the HSD. In a similar manner, as illustrated in Figure 4.3, the starting date for the HSD was on 1 November 2010, which also falls within the period of the lost decade of the JSE. The GARCH (1, 1) model captured one distinct feature that the HSD fell short of illustrating. This feature was the non-constant volatility, which the GARCH (1, 1) model was able to demonstrate during highly volatile periods that were characterised by extreme events. This was also referred to as the tendency of large changes in the share price returns to cluster together, whereby a continuous persistence in such changes affected the economy (Cont, 2007). These large changes or share price spikes, which were recorded on 20 May 2010, 06 May 2015, 11 December 2015, and 23 March 2020, drew in similar dates to those from the EWMA model in Figure 4.3. The mid-cap share index was vulnerable to the negative consequences of load shedding in 2019; the South African economy lost at least 118 billion rand due to load shedding (Burkhardt, 2020).



Figure 4.5: Extreme events for mid-cap shares

When clustered together as a result of extreme events, the large changes in volatility clustering of share price return leave behind an economy that will take a long period to recover. In an already falling economy, extreme events put further strain on monetary and fiscal policymakers (Ugwuanyi & Nwaocha, 2019). It is the objective of every country to move forward and restore the economy to good shape and any changes that it takes to restore the economy to its rightful place should prioritise foreign direct investments and growth in GDP.

The financial crisis of 2008/09 negatively affected mid-cap shares, as they declined from 372 rand on 23 May 2007 to 217 rand on 27 October 2008. Extreme values for mid-cap shares amounted to 1.45 per cent and 1.53 per cent during the period 02 January 2007 to 31 July 2020. The percentage of 1.53 was determined using the standard normal distribution. Meanwhile, the percentage of 1.45 was determined using the 95 per cent confidence interval. Figures 4.6 and 4.8 featured extreme values of mid-cap shares using the EWMA and GARCH (1, 1) models. A pattern of various extreme events was captured, which further illustrated an inverse relationship between volatility and share price returns.

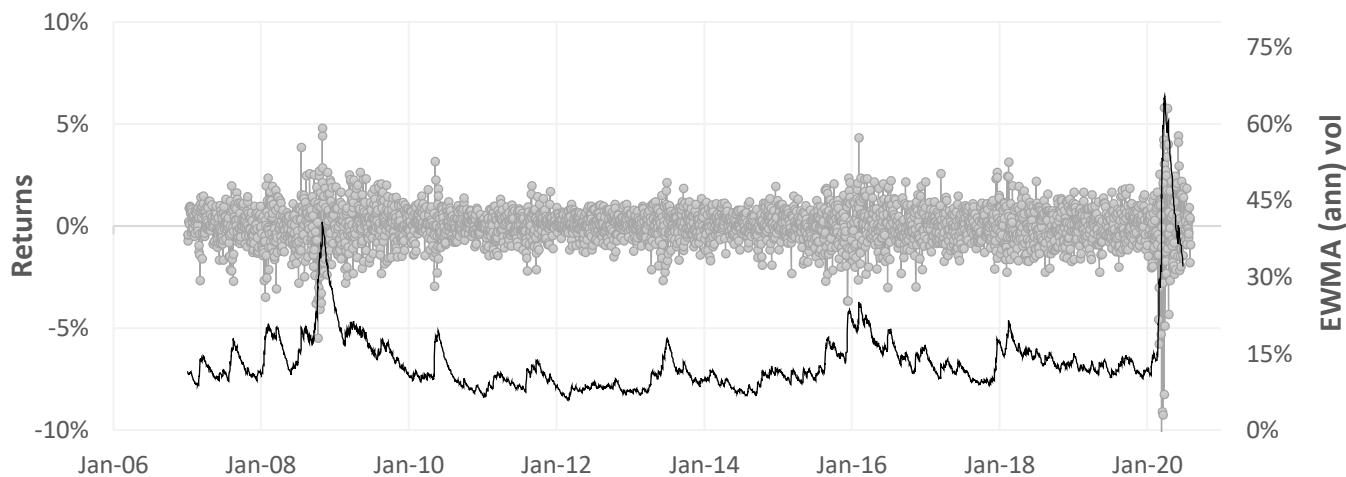


Figure 4.6: Extreme values using EWMA model for mid-cap shares

Share price return for the period 2 January 2007 to 31 July 2020 averaged negative 0.80 per cent whereas the EWMA model volatility continued to showcase extreme events as discussed in Figure 4.5. During the financial crisis of 2008/2009, share prices declined from a high of 300 rand on 18 March 2008 to 260 rand on 16 February 2009. Meanwhile, their share price returns were at 1.44 per cent and negative 0.99 per cent, respectively. The COVID-19 global pandemic contributed to an unfavourable major shift in the mid-cap financial markets, whereby the share price returns on 23 March 2020 were reported at negative 8.23 per cent.

On 18 March 2008, and 11 December 2015, the annualised volatilities were at 20.2 per cent, and 22.4 per cent, respectively, when factoring 250 trading days in a year. Likewise, after 23 March 2020 the announcement of the 21-day lockdown to stop the spread of COVID-19, a negative relationship between share price returns and volatility was unavoidable as the annualised volatility was at 64.2 per cent, while share price returns were at negative 8.23 per cent.

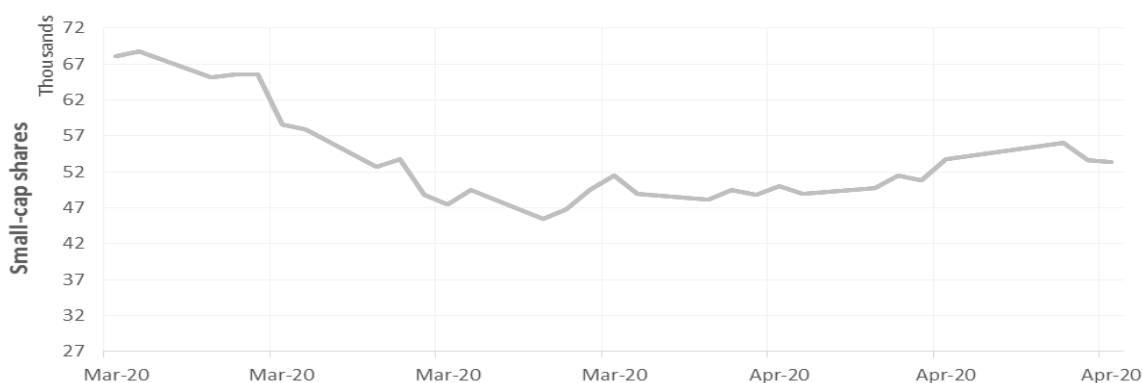


Figure 4.7: Mid-cap shares movement during the 21-day lockdown in South Africa

The global unrest that was caused by the COVID-19 pandemic was a major causation of the mid-cap share trend in the 21-day lockdown, as depicted in Figure 4.7. Mid-cap shares were at their

highest at 688 rand on 6 March 2020, which was 17 days before the official announcement of the lockdown. However, due to panic selling of shares by mid-cap share investors who were driven by fear, and overreacting to the news pertaining to the global pandemic, a downward trend of share prices followed whereby on 23 March 2020, share prices hit their lowest at 454 rand (Krugel & Viljoen, 2020). A percentage change between the highest and lowest share price stemmed as a result of panic selling at negative 51 per cent. Following the announcement of the 21-day national lockdown by President Cyril Ramaphosa, the mid-cap share index performed relatively well, as companies began to profit during the crisis. From 23 March 2020 to 26 March 2020 shares increased by 13 per cent, however, the percentage change increase was short-lived, as on 27 March 2020, which was the official first day of the lockdown, shares declined to 490 rand. In addition, as the companies were adhering to the health guidelines and industrial classification systems, which stipulated the industries that were eligible to resume operations, and to what extent they were to function, the mid-cap share index was forward-looking (Truter, 2020).

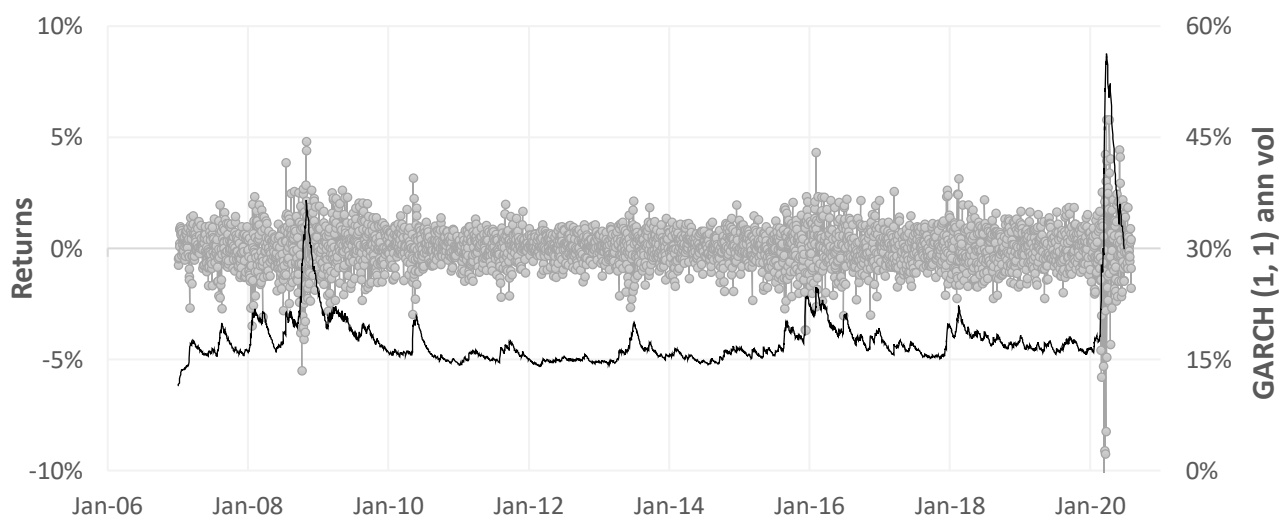


Figure 4.8: Extreme values using GARCH (1, 1) model for mid-cap shares

In Figure 4.8, the annualised GARCH (1, 1) model volatility for mid-cap shares depicted an inverse relationship with the share price returns. An average of the share price throughout the period from 2 January 2007 to 31 July 2020 was at 546 rand, whereas the spikes in volatility were captured on specific dates namely, 6 October 2008, 11 December 2015, and 23 March 2020 due to the 2008 financial crisis, as well as the ongoing Eskom load shedding. In addition, the political climate, the downgrade of South Africa’s investment grade by Fitch to an unfavourable investment grade of negative BBB, and the COVID-19 global pandemic were also captured on the aforementioned dates (Stanlib, 2017). The annualised volatilities on those dates were at 26.9 per cent, 22.9 per cent, and 55.2 per cent, respectively.

Up to this point, mid-cap shares had been captured because of the negative relationship between share price returns and volatility as influenced by the models in Figures 4.2, 4.3, 4.4, 4.6, and 4.8. The sampling period end date on 31 July 2020 was important in calculating the optimal lambda which was followed by a one-day volatility forecast at 0.51 and 0.79 for the EWMA and GARCH (1, 1) models, respectively, given the encountered COVID-19 extreme event.

4.5 CONCLUSION

The study aimed at determining which model between the EWMA and the GARCH (1, 1), was best at forecasting volatility in mid-cap shares. This was done by taking into account the mid-cap share index J201. It was followed by determining the optimal lambda at the end of the sampling period on 31 July 2020, whereas the optimal lambda was calculated to be 0.974. The value of 0.974 was factored in both models, in proceeding with the analysis. The study revealed four key findings, as summarised in the following paragraphs.

Firstly, the optimal lambda showcased its relevance in the EWMA model and share price weighting. It played a major role in the weighting of share prices when they were rearranged, as more weight was provided to recent share price returns and less weight was provided to distant share price returns. The model was able to track specific periods under analysis, which were visible to the aggressiveness of share price return movement and volatility. Meanwhile, the application of equal-weighting in the HSD was a limitation in the capturing and recording of extreme events. Furthermore, when the value 0.974 was decreased, more weight was applied to, specifically when approaching the end period. The value was also determined as an optimal lambda as of 31 July 2020. Including this value demonstrated how volatility was affected. Meanwhile, the overall risk of investment in mid-cap shares was lower than that of large- and small-cap shares. This was based on the aspect that mid-cap shares were positioned to take advantage of small and large-cap shares and viewed effectively for long-term growth-share investment.

Secondly, the GARCH (1, 1) model factored in three weights, which were significant towards the model's long-run variance. The model's quick rate of readjusting to the effects of share price shocks during extreme events was displayed in the Figures above, whereby large changes in share price returns shifted from positive to negative during an extreme event and, meanwhile, volatility shifted from negative to positive, and depicted an inverse relationship between share price return and volatility. The model readjusted to a moderate movement in shares, following COVID-19 outbreak and panic selling by investors, as the magnitude of the extreme event was large. The unfavourable share price returns that were caused by heightened political risk and a downgrade of South Africa's sovereign credit rating during the month of December 2015, discouraged foreign

direct investment, which would have contributed positively to an underperforming economy. Furthermore, the announcement of the 21-day national lockdown on 23 March 2020, due to COVID-19, caused the highest volatility, as captured by both GARCH (1, 1) and EWMA models, at a cost of returns in mid-cap shares. After the announcement of the lockdown, volatility was at its highest in the period under analysis. This highlighted the riskiness of investing in shares and the need for a diversified investment portfolio.

Thirdly, the HSD was not able to capture volatility at a similar level as of the two models, specifically during the COVID-19 extreme event and aforementioned aspects that led to the discouragement of foreign direct investments. This inability revealed its shortfall and deprived investors of a holistic view and analysis of share price returns. The HSD did not track a volatility movement similar to that of the two models. This was based on the use of the EWMA and GARCH (1, 1) models' optimal lambda and the respective equations that make up each model. The HSD model, as a measure of risk, also adhered to the negative relationship of share price returns and volatility. However, solely using the HSD model in volatility forecasting showed more of its shortfalls, such as investors timing to sell shares when it was necessary, in order to minimise the losses that stemmed from the COVID-19 extreme event.

Finally, the variations in the EWMA and GARCH (1, 1) models were based on volatilities and their dominance in continuously updating forecasts, subject to availability of new information. The quick rate of readjusting to effects of mid-cap share price shocks, influenced the decision to use the models instead of solely using the HSD. The choice of the most preferable model was based on investors' ability to comprehend the costly use of the GARCH (1, 1) model for the implementation and processing of large data. Additionally, the usage of the EWMA model was influenced by its ability to minimise errors in volatility forecasting through considering previous errors in forecasting, after which the accuracy was improved in the follow-up forecast. The decision was also based on the key weakness of the HSD of assigning the same weight in which the previous day's share price return did not affect the variance distant period return. The two models improved on this weakness by providing more recent share price returns with greater weight on the variance.

4.6 RECOMMENDATIONS

As the study was mainly focused on forecasting volatility using the EWMA and GARCH (1, 1) models, it is recommended that the other models that also point out the assigning of the same weights of share price returns for the HSD model should be used in volatility forecasting.

4.7 LIMITATIONS

Despite the unfavourable investment grade of negative BBB assigned by Fitch Ratings due to weak economic performance and the impact of the outbreak of COVID-19 on mid-cap shares and optimal lambda that took place in the period under analysis, other factors leading to the underperformance of the South African mid-cap shares proved to be the limitations of the study.

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CHAPTER 5: CONCLUSION AND SUGGESTIONS FOR FUTURE RESEARCH

5.1 SUMMARY AND CONCLUSIONS

As stated in Chapter 1, the primary objective of the study was to forecast volatility in small and mid-cap shares using the EWMA and GARCH (1, 1) models. The standard deviation was viewed as the most preferred measurement of volatility despite its weakness of assigning equally-weighted share price returns.

5.1.1 Theoretical objectives

In order to achieve the primary objective, the following theoretical objectives for article one and two were formulated for the study:

1. Contextualise the significance of volatility forecasting of asset returns in small and mid-cap shares to investors share portfolio construction;
2. Emphasis on the benefits and drawbacks of the EWMA and GARCH (1, 1) models;
3. Identify the event that caused extreme volatility during 01 January 2010 to 31 July 2020 and;
4. Investigate the factors that led to the underperformance of small and mid-cap shares.

5.1.2 Empirical objectives

The **empirical objective**, which identified the relationship between the EWMA and GARCH (1, 1) models using daily data, displayed that both models overcame the weakness of the standard deviation in which share price weights declined exponentially as considerable share price weights were assigned to latest dates and smaller weights were assigned to more distant dates. Chapter 1 provided an introduction and background to the study and the research problem statement. Furthermore, the outbreak of COVID-19 displayed the manner in which small, and mid-cap share volatility performed with reference to their respective share price returns using the EWMA and GARCH (1, 1) models. The forecasting of volatility by 31 July 2020 was also conducted through the consideration of investing in small and mid-cap shares, which provided a significant alternative from the Top 40 shares.

Small and mid-cap shares were more volatile, thus, implying a comprehensive fundamental analysis in choosing shares that were undervalued. In addition, two types of investors namely, limited in-depth knowledge investors and risk averse investors, often depended on disregarding small and mid-cap shares because of their high volatile behaviour and opted for the Top 40 shares.

From 2010 to 2020, the Top 40 shares were more popular for reflecting the South African market and represented over 80 per cent of the total market cap of all JSE listed companies. Small and mid-cap shares were more focused on the local economy, however, heightened political risks, the downgrading of the investment grade by Fitch credit ratings, and the mounting pressure of managing the outbreak of COVID-19, which was first recorded in South Africa in March 2020, discouraged confidence in the likelihood of economic growth. The classification of COVID-19 as an extreme event fulfilled another **empirical objective**, as the pandemic had a low probability of occurring. However, as it took place, it led to a great damage to the global economy. Using the EWMA and the GARCH (1, 1) models showcased distinct variations in volatility forecasting trends in small and mid-cap shares.

The distinct volatility forecasting trends for small and mid-cap shares was fundamental for their respective varying optimal lambdas and characteristics. In spite of both shares aligning with the theory of the negative relationship between volatility and share price returns, a higher risk was expected in small cap shares than in mid-cap shares. Both small and mid-cap shares also adhered to volatility clustering as sizeable changes in share price returns were instantaneously followed by sizeable changes of similar share price returns, which also applied in the case of small changes in share price returns. Both models also tracked a relatively similar movement in volatility for small and mid-cap shares based on similar extreme events. However, the riskiness of investing in small cap shares was evident when comparing the models in relation to those from mid-cap shares.

In all instances, the small-cap share price volatility was higher than that in mid-cap shares, when using the EWMA and the GARCH (1, 1) models, specifically during the COVID-19 extreme event. This added to the analysis that small-cap shares were not only riskier investments, but also, they showcased greater growth potential, while providing better returns over the long term irrespective of falling short of equipped resources than mid-cap shares. The **empirical objective** for the calculated optimal lambdas by 31 July 2020 – the end period of the study analysis, it was fulfilled since the mid-cap optimal lambda was of a more considerable size than that of small-cap shares. This was due to the considerable share price weighting as each weight was a constant multiplier of the prior day's weight. The need to forecast volatility in small and mid-cap shares using the EWMA and GARCH (1, 1) models was stated and motivated. Following the stated primary objective, empirical objectives and problem statement, the theoretical objectives were also formulated to achieve the purpose of this study.

5.1.3 Article 1: Volatility forecasting during extreme market events using the small cap share index

Following the equity investments plummet in the 10-year period to what was known as the lost decade of the JSE for small cap shares, it was evident that a consideration of the EWMA and the GARCH (1, 1) models was needed in forecasting share price volatility. The **fourth theoretical objective** aimed at investigating factors that led to the underperformance of small and mid-cap shares was achieved as follows: rising government debt, inconsistency in the South African electricity public utility named Eskom, and a discouraging performance of GDP were among external factors which contributed to declining investments in small cap shares. Also, failure to comply with corporate governance was perceived as an internal factor to this phenomenon.

The **third theoretical objective** was achieved as both the EWMA and the GARCH (1, 1) volatility forecasting models were appropriate for use in the extended analysis period in order to cover the outbreak of the COVID-19 global pandemic and its impact towards the optimal lambda and the performance of small cap shares. The outbreak of COVID-19 negatively affected small cap shares, as was proven at specific periods approaching 31 July 2020. The lockdown announcement further caused panic selling of shares while pandemic proof small cap companies benefited from the outbreak of COVID-19. The **first theoretical objective** was aimed at small cap shares, which were commonly known for their high level of risk and volatility. Conservative investors preferred a stable investment, which grew steadily over time, thus, considering a small portion of this type of an asset class in their portfolio. Meanwhile, unlike their conservative counterparts, aggressive investors often used volatility-forecasting models in order to make informed decisions for the right time to sell their small cap shares, which subscribed a large portion to their investment portfolio.

Following the variations between conservative and aggressive investors and factoring in potential small cap share investments, holding this type of shares had several benefits, thanks to the effective use of both models. Investing in small cap shares was hampered by investments limited research, conducted because of few analysts covering them, in an extreme event such as that of COVID-19, given that very few analysts were dedicated to covering the portfolio. However, in an extreme event, such as COVID-19, conducting a thorough research for identifying undervalued shares made provision for a competitive advantage over large cap shares, which normally had a large number of analysts, and fund managers working on various investment portfolios. Meanwhile, the inexpensiveness and rapid rise of small-cap shares signified a greater return of investment.

The presence of EWMA ensured that, while using daily data to calculate the optimal lambda, the model continuously updated its forecasts as new information became available. Meanwhile,

overseeing volatility clustering using the GARCH (1, 1) model played a significant role in these types of shares hence; both models fulfilled the **second theoretical objective**. The primary objective of the study was satisfied, as both volatility-forecasting models illustrated their superiority over the HSD model and managed to capture the effects of the COVID-19 extreme event on small-cap shares. The use of both models was suggested and prioritised for continuous volatility forecasting of daily small-cap shares.

5.1.4 Article 2: Volatility forecasting during extreme market events using the mid cap share index

Mid-cap shares were not exempted from the share investment decline throughout 01 January 2010 to 31 December 2019 as they also formed part of the lost decade of the JSE. Their exposure, due to being majority domestic companies, coupled with mismanagement, incompetency, failure to uphold effective and ethical leadership, towards achieving governing outcomes for smooth corporate operations were the major drawbacks. Because of the aforementioned drawbacks, the respective companies lacked good performance, effective control, and legitimacy, thus, achieving the **fourth theoretical objective**. However, as the study displayed, the categorised positioning of mid-cap shares, which falls between volatile small-cap shares and large cap stability, made them suited for long-term growth. The incompetency of the HSD model in volatility forecasting including the period that analysed COVID-19 and the optimal lambda, highlighted the need to consider using the more effective EWMA and GARCH (1, 1) models. The **third theoretical objective** was achieved as both models were selected as they captured and pursued COVID-19 as an extreme event, in which the HSD was unable to do.

The presence of both models was useful for investors that were well positioned to exit the market at the right time to safeguard their investments, which were negatively affected by the outbreak of COVID-19 and those that were not immune from it. Nevertheless, the inclusion of mid-cap shares in an investment portfolio was beneficial provided fundamental analysis was conducted and a shift in categories from mid-cap to large-cap shares indicated greater investment returns for early investors that had been with various mid-cap companies throughout the COVID-19 extreme event. This was well illustrated by high quality management teams that were well suited for identifying undervalued shares. Undervalued shares were more of a prospect for new investors, as their approach was drawn from the knowledge that an increase in asset value over time, because of high demand will endure expected higher investment returns that will be added in the investment portfolio, thus fulfilling the **first theoretical objective**.

Nevertheless, using daily data for determining the optimal lambda of mid-cap shares, the behaviour of the EWMA model was similar as to that encountered in the analysis of small-cap shares. The **second theoretical objective** was achieved through emphasising the benefits and drawbacks of both models. This was as follows: the EWMA model considered its sustained manner for updating volatility forecasts, while the latest COVID-19 information heightened political risks and unfavourable credit ratings. This fundamental characteristic of the EWMA model was evident in both small and mid-cap shares. Simultaneously, the GARCH (1, 1) model was in effect, as it provided a more real-world context in forecasting mid-cap share volatility, despite its high-priced usage as it discouraged investors who could not bear the costs and, in turn, such investors preferred the EWMA model.

5.2 PREVIOUS STUDIES

Previous studies focused on the moving averages and the autoregressive conditional heteroskedasticity forecasting models including the EWMA and GARCH (1, 1) models. Previous studies also focused on the entire stock market and the exchange rate volatility, rather than the small and mid-cap shares, as was the case in this study. The preference of the EWMA model to the GARCH (1, 1) model was subjected to the analysts' knowledge and skills to conduct forecasting and aforementioned computational expensiveness of their operation. The primary objective of the study was met, however, suggestions for future research denoted the study's limitation, and expanding on other volatility forecasting models that were not used in this study.

5.3 SUGGESTIONS FOR FUTURE RESEARCH

The impact of the COVID-19 pandemic on the optimal lambda was notable, as it was significantly affected, having been factored in respective equations of the models. For this study, the period under analysis ended 31 July 2020, which could be extended in future research, taking into account the entire period of the COVID-19 extreme event would have affected the economy, including the small and mid-cap shares. This would provide another perspective in identifying the periods when various types of investors, i.e. conservative or aggressive, prefer to buy and/or sell their shares, if they use the EWMA and GARCH (1, 1) models. Additionally, it would make provision for a holistic view of the performance of small and mid-cap shares for their high levels of risk, when compared to large cap shares, in which more attention for further analysis by fund managers, analysts, and individuals who are interested in investing would have an opportunity to conduct both fundamental and technical analysis. Furthermore, previous studies were prioritised on large cap shares, instead of small and mid-cap shares, and as such, further research can be conducted on

the latter, thus, providing an interesting and holistic view for investments in those aforementioned shares (small and mid-cap) for volatility forecasting.

Other models, which belong to the moving averages and autoregressive conditional heteroskedasticity families, could be used in determining variations in the optimal lambdas of small and mid-cap shares. Furthermore, such models can be used in gauging the extent of volatility forecasting while analysing the share price volatility and returns. The study could conduct an analysis solely of the Top 40 JSE listed shares or the all-share index using either daily or monthly data forecasting, thus, adding to the importance of the highlighted volatility forecasting models.

ANNEXURE 1

Sune Ferreira - [AUDOE] Editor Decision

From: Daniela Monica Robu <danubiusjournals@univ-danubius.ro>
To: Sune Ferreira <23261048@nwu.ac.za>
Date: 2021/03/15 08:43
Subject: [AUDOE] Editor Decision

Sune Ferreira:

We have reached a decision regarding your submission to Acta Universitatis Danubius. Economica, "ANALYSING VOLATILITY DURING EXTREME MARKET EVENTS USING THE MID CAP SHARE INDEX".

The article will be published in our journal if the following revisions are successfully implemented:

- arrange the article according to the template, in terms of page format, and text requirements;
- revise English usage;
- see below.

Please submit the final version of the article with all the data of the authors according to the template provided on the home page of the journal at Author Guidelines by the end of March 2021.

Sending the Revised File #

Please send by e-mail the final version of the article, as a reply to this message.

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Reviewer A:

Recommendation: Accept Submission

Abstract and Introduction

Comments/Rate:

Abstract and Introduction are well synthesized and in correlation to all content of the article.

Methodology

Comments/Rate:

The Methodology of this study is a descriptive research approach, a qualitative research with the models EWMA and GARCH who are appropriate for daily data as they make provision for accurate forecast of volatility after day $n-1$.

Scientific results

Comments/Rate:

Scientific results can provide the optimal lambda factored in the calculation of the EWMA and GARCH forecasting after day $n-1$. While investments in small-cap were of fast growing companies under the equities asset class, they were deemed favorable for their potential of being undervalued and outperforming the market during the recovery from Covid-19. Meanwhile, mid-cap shares were also favored for their positioning. Mid-cap shares were regarded as less-volatile compared to small-cap shares, moreover, they reflected more growth potential than large-cap shares. EWMA and GARCH (1, 1) were set up against the historical standard deviation. The historical standard deviation was applied to identify its weakness in

mid-cap shares whereby similar share price return weights were tracked in the period of the last decade of the JSE and the beginning seven months of the year 2020 when Covid-19 was in full operation.

How do you rate the English usage?

Satisfactory

Final Comments/Rate

The article can be accepted to be published.

Reviewer D:

Recommendation: Accept Submission

Abstract and Introduction

Comments/Rate:

Abstract is relevant for the papers and the introduction is presenting the context of the study.

rate - good

Methodology

Comments/Rate:

the methodology is in accordance with the research.

rate - good

Scientific results

Comments/Rate:

The results are robust and very well presented

rate - good

How do you rate the English usage?

Satisfactory

Final Comments/Rate

The paper is approaching and analyzing a actual subject with new methods.

The paper is well structured and the results and findings detailed presented.