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Analysing Volatility during Extreme Market Events Using the Mid Cap Share Index

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Abstract: The JSE underperformance in 2010 to 2019 as a consequence of a collapse in mid-cap share investments signified a 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 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 using the exponential weighted moving average and the general autoregressive conditional heteroscedasticity using the mid-cap share index (J201). Furthermore, the study aims at calculating the optimal lambda during the Covid-19 global pandemic. The models examined the negative relationship between share price returns and volatility during extreme events which led to fat tailed distribution of returns in share price returns. On December 2015 an unfavourable South African investment grade of negative BBB was assigned by Fitch Ratings and the days following the Covid-19 lockdown, share price returns plunged encouraging panic selling by risk averse investors.

Keywords: JSE underperformance; Covid-19; share price returns

JEL Classification: G01; G11; G17

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, making up 60 companies tracked in the mid-cap share index (J201). These shares had gained momentum from investors for inclusion in an investment portfolio following the 2008 financial crisis (Ashburton Investments, 2020). Their performance was more

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favourable in comparison to the small and large cap shares during the period of the financial crisis (le Roux, 2018). Mid-cap shares were at negative 17.81 per cent, 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 consist 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 level of stability in returns for investors, meanwhile, reflecting 80 percent of the total market capitalisation of all JSE listed companies, risk averse investors are inclined to invest in large cap shares and keep away from mid-cap shares (Rizal *et al*, 2018).

Furthermore, mid-cap shares tend to recover much slower than small-cap shares after each economic downturn (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 (Klein, 2019). The top quality management team provides an opportunity to identify undervalued liquid shares that are incorrectly priced by the market (Doukas *et al*, 2010). Also, it becomes manageable to sell shares before a market downturn. Montag and Caldwell (2020) showcased that in the period under the study analysis, mid-cap companies were safer for investing because they fall between the volatile small cap shares and large cap share stability meanwhile, providing assurance for long-term growth. Their value increase with time whereby 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, they 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 volatility in relation to mid-cap share price return using the EWMA and the GARCH (1, 1) models. Such 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 provided the underperforming South African economy's impact on mid-cap companies (Cotterill, 2020). The objective of the article is therefore to examine and forecast mid-cap share volatility during extreme events using the EWMA and GARCH (1, 1) models using the mid-cap share index (J201). To conduct an analysis on daily share prices from 1 January 2010 to 31 July 2020, considering extreme events that occurred during the period named the lost decade of the JSE and the analysis on a global pandemic coronavirus. It follows the calculation of an optimal lambda that is affected by extreme events for the specified period as identified in the respective models.

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 R1 billion and R10 billion. Whereas small-cap and large cap shares consist of market capitalisations that are below 1 billion and over 10 billion rands respectively (JSE, 2020). The mid-cap index is a representative of 85 percent to 96 percent of the full market cap value of all qualified ordinary securities listed on the main board of the JSE (JSE, 2020). As a way to raise capital, mid-cap companies sell shares instead of taking debt so that they continuously grow while attracting potential investors (Kim & Weisbach, 2005).

In conducting market research, potential and active investors will find important features making up mid-cap shares. These shares are diverse as they are characterised by companies that offer long term stability and those that have recently moved from small-cap allowing greater returns (Reeves, 2020). Their ability of becoming less volatile compared to small-cap shares while remaining more volatile to large cap shares during market contraction, together with their innate liquidity allowing a moderately easier transaction during a sale of shares at a fair price is a feature an investor should be aware of (Amadeo, 2020). Mid-cap shares might not be as exciting as small-cap shares that recently received their initial public offering (IPO) however they are thoroughly researched as much as their counterparts in large cap shares. As such, mid-cap shares are not as risky as their small-cap counterpart 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 stability (Wisdomtree, 2018).

Mid-cap companies have attracted potential and active investors as they are positioned in the boarder and exploit both ends of small and large cap shares. They find themselves in a less volatile path as they had proved to have moved past the riskier shares in small-cap companies and geared towards long term growth (Kumar & Misra, 2015). For that reason, investors will benefit from a number of advantages. Provided that they are positioned as mid-cap shares, they allow for stock appreciation, whereby assets value increase over time due to their increase in 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 of being overlooked because of limited attention from large institutions. This leads to low pricing allowing investors to include these shares in their investment portfolios (Muller, 2019). Despite this, mid-cap companies do 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 for their ability to withstand economic downturns such as the financial crisis and the coronavirus pandemic (Vovchenko *et al*, 2017). In the interest of having a balanced understanding of mid-cap shares, these companies are not immune from the following disadvantages.

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 in relation to those of industry competitors. This poses a threat whenever the share price continues to decline significantly when such investors have already bought into the mid-cap companies, trapped in a company that operates in low profits that functions with 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 poses a threat. This is problematic because small-cap companies moving up the ranks experiencing exponential growth with increasing market capitalisation will see such stagnant mid-cap companies moving down the rankings and labelled as the next small-cap companies (Martin, 2019). Likewise, they are also prone to any financial bubble as when it occurs it 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.

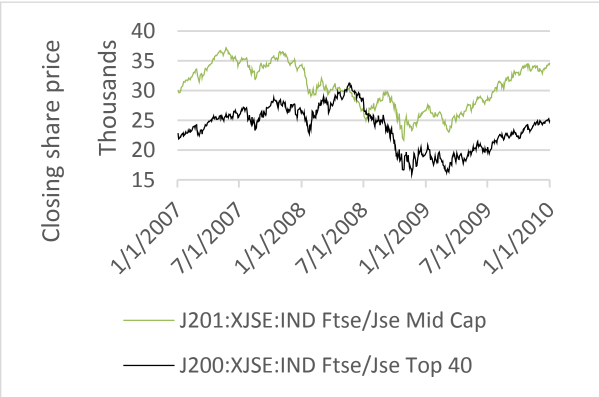

Figure 4.1. Behaviour of Mid-Cap Share Prices Against the Top 40 Companies during Recessions and Recoveries

Source: IRESS INET BFA (2020)

Figure 4.1 represents the performance of the share prices of the JSE Top 40 and that of mid-cap companies. During the period 23 May 2007 and 27 October 2008, mid-cap shares were at 372.28 and 216.81 rands 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 rands respectively. Also, JSE Top 40 shares encountered a negative percentage change of 36.08 per cent. During the period outlined, both mid-cap and JSE Top 40 shares undergone a significant decline in share prices. Moreover, the JSE Top 40 share had the highest share price on 26 May 2008 at 308.01 rands meanwhile the mid-cap highest recorded share price was captured on 23 May 2007. Likewise, more investors bought shares than sold them causing a rise in share prices. While mid-cap shares resemble qualities of small and large cap shares, their rise in a recovery phase is not at a quick rate as the small cap shares irrespective of a larger decrease during a recession. Nonetheless, they still reflect attractive value appreciation and so as both small and large cap shares, their performance grows during the expansion phase of the business cycle. Quarterly gross domestic product growth in second and fourth quarter in 2007 was at 0.8 and 1.4 percentage respectively (Country economy, 2007). In the case of mid-cap companies, capital is inexpensive which places the management team at a position of investing in capital equipment, or perhaps they could focus on merging with another company that shares similar values and acquire start-ups which indicate potential growth (Amadeo, 2020). The type of investors likely to buy into mid-cap shares are seasonal. They are discussed as follows.

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) defines a seasonal investor as an individual that narrows focus on volatile markets, whereby companies are dynamic and technology is advancing while holding the view of uncertainty as an important key element in the long-term. A seasonal investor might be discouraged by mid-cap companies that do not seek to grow and move from the mid-cap index to the large cap index. Seasonal investing is effective when used with fundamental and technical analysis and timing the market can be a disadvantage when not used effectively as it is key to maximum profits (Kulp, 2019). A seasonal investor can be discouraged by time consumed on thoroughly staying updated on latest trends. Nevertheless, these type of investors are driven by easily available data as historical trends and performance of shares are tracked from the past which give an overview of 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. Buying mid-cap shares at the commencement of the trend and selling by the end period of the trend at a higher share price is common for reaching maximum profits (Shim, 2000).

3. Methodology

IRESS INET (Pty) Ltd an online tool is used to obtain financial data 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 Covid-19 otherwise known as the coronavirus which is discussed with respect to 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 realised based on the share prices of mid-cap companies which undergone a steep decline. Meanwhile on 31 December 2019 shares were trading at negative four percent. Daily returns are determined on the aspect of information that stems from low frequency trends in volatility specifically in a crisis using daily data (Danielsson *et al*, 2018). The models EWMA and GARCH (1, 1) are appropriate for daily data as they make provision for accurate forecast of volatility after day n-1 (Guo, 2012).

Methodology is subjected to historical daily data and in using these two models. For the highlight of the models, they are derived as follows.

3.1. Forecasting Volatility

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 for the entire period that was a year and six months i.e. 01 January 2010 to 31 July 2020, and in the attainment of empirical objectives for the study. The section was broken down into the EWMA section 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:

$$u_i = \ln(\frac{S_i}{S_i - 1})$$

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

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

$\overline{u})^2$ (1.1.)

Whereby u bar implied the mean of the u_i's:

$$\overline{u} = \frac{1}{m}\sum_{i=1}^{m} u_n - i$$

The above formula $\overline{u}$ was modified on the basis of the study analysis using daily volatility, 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

$$u_i = \frac{S_i - S_{i-1}}{S_{i-1}} \quad (1.2.)$$

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

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

$$\sigma_n^2 = \frac{1}{m}\sum_{i=1}^{m} u_{n-i}^2 \quad (1.3.)$$

Whereby u_i was provided in (1.2).

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

$$\sigma_n^2 = \frac{1}{m}\sum_{i=1}^{m} \alpha_i u_{n-i}^2 \quad (1.4)$$

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 which transformed the model to a new form which was as follows

$$\sigma_n^2 = \gamma V_L + \sum_{i=1}^{m} \alpha_i u_{n-1}^2 \quad (1.5)$$

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

$$\sigma_n^2 = \omega + \sum_{i=1}^{m} \alpha_i u_{n-1}^2 \quad (1.6)$$

In accordance to equation (1.4) and (1.6), various approaches were implemented to track volatility. These approaches are EWMA and GARCH (1, 1) models.

EWMA model was shown in equation (1.4). 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 as follows:

$$\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1-\lambda)u_{n-1}^2 \quad (1.7)$$

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

Adewuyi (2016) points out that 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 (1.7) volatility forecast progressed upward. Meanwhile, lambda was responsible for the responsiveness of daily volatility forecast subjected to the leading percentage change (Finance Train, 2020). In addition, a higher weight provided to u_{n-1}^2 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 was 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 with respect to the GARCH (1, 1) model was as follows:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta\sigma_{n-1}^2 \quad (1.8)$$

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

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta\sigma_{n-1}^2 \quad (1.9)$$

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. Results and Discussion

The objective of the study is to analyse the optimal lambda factored in the calculation of the EWMA and GARCH (1, 1) forecasting after day $n - 1$. While investments in small-cap 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. 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 lost decade of the JSE and the beginning seven months of the year 2020 when Covid-19 was in full operation.

In agreement with the theoretical objective which puts forward the importance of volatility forecasting of share price returns in mid-cap shares and the drawbacks namely, the inability to recover at a quick rate from large shocks as an event that occurred on the EWMA meanwhile such was a benefit for the GARCH (1, 1) model whereas it normally readjusted at a quick rate to the effects undergone in the JSE. The identified extreme events were discussed in a broader sense that the models played a significant role for share investment construction made by active and potential investors than to have a limited view of only taking into account the historical standard deviation which was explored for its major drawback as discussed above. Table 4.1 and Figure 4.2 to 4.8 are in alignment with chapter 1 empirical objectives which among others indicated whether Covid-19 could be categorised as an extreme event and the exploration of the relationship between EWMA and GARCH (1, 1) models using daily data was conducted. Furthermore, a sample of ten companies categorised as mid-caps and used in the mid-cap index (J201) were 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**									

***Significant at 1%*

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. Also, 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 model and the GARCH (1, 1) model against the mid-cap share price returns were made and the gathered analysis proceeded.

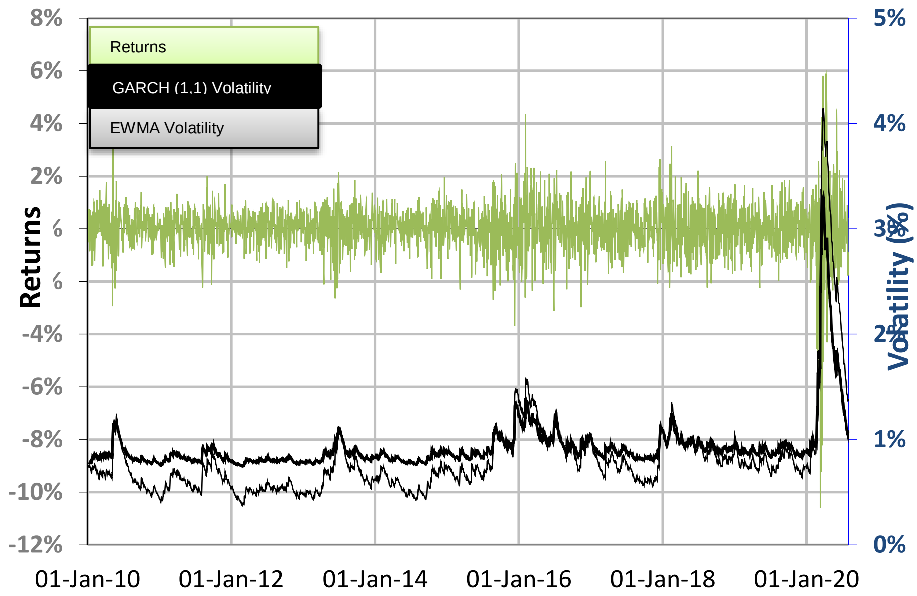

Figure 4.2. Comparison of the Exponentially Weighted Moving Average and General Autoregressive Conditional Heteroskedasticity (1, 1) volatilities for mid-cap shares

The EWMA and the GARCH (1, 1) showcased a relative movement of volatility which was well captured during the periods of high and low volatility. EWMA factored in the optimal lambda of 0.974 whereby data was expressed in daily terms. 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 as to realise the variation from using the historical standard deviation 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 arriving at the value of zero, the weight on recent share price returns increased, meanwhile, the weight on distant share price returns decreased. When 0.974 was adjusted arriving at the value of one, recent share price return weights declined and those that were distant grew. Furthermore, any adjustment of 0.974 share price return weights always added up to 100 per cent, however, with an exception of 0.974 adjustment 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 GARCH (1, 1) was presently used to also note its disparity with the historical standard deviation and EWMA.

GARCH (1, 1) model had three recognisable weights namely, beta, gamma and alpha which both had the value of 0.013 respectively, 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 to that of EWMA in forecasting volatility up to the date 31 July 2020.

The presence of both models were 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 composed of less risk in comparison to small-cap shares (Brink, 2020). A short-term spike in share price volatility was captured by both models on 11 December 2015 whereby the share price returns dipped to negative 3.67 per cent and the EWMA and GARCH (1, 1) 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 on other periods when extreme events took place. Figure 4.4 looked into the variations between the exponentially weighted moving average and the historical standard deviation in which the historical standard deviation was not capturing shocks in share price volatility.

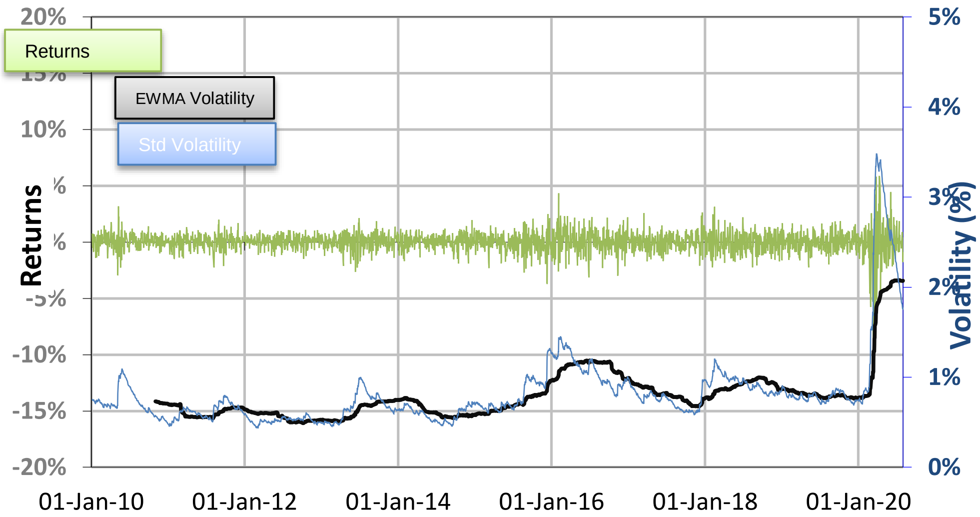

Figure 4.3. Variations of the Exponentially Weighted Moving Average (EWMA) and the Historical Standard Deviation for Mid-Cap Shares

Figure 4.4 shows a different volatility trend between the historical standard deviation and the EWMA. The starting date for the historical standard deviation on 1st November 2010 was chosen because of the lost decade of the JSE largest share price recorded at 12 per cent and its calculation was captured from the 4th of January 2010 to 1st 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 respectively.

EWMA 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 based on competitive pressures. Haasbroek (2020) provided an example of one of the mid-cap companies Spur Corporation Limited, as a restaurant company, it suffered from Covid-19 as the share price was 15.50 rands on April 2020, a decline of 41.8 per cent from the beginning of January 2020. On 20 May 2010, the share price return was at negative 2.27 per cent and a volatility of 1.04 per cent. This was further influenced by a 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 EWMA 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 a credit rating agency named Fitch Ratings responsible for providing ratings towards the application of investments relative to the probability of default (Teixeira, 2020).

Fitch Ratings downgraded South Africa's sovereign credit rating from BBB to BBB- whereas BBB- is categorised in the lowest investment grade (Fitch Ratings, 2020). SARB (2017) pointed out that the downgrade was influenced by a slow economy as the real growth rate was at 1.3 per cent whereby in 2014 and 2013 real growth rate was at 1.5 and 2.2 per cent respectively. On the other hand, after the announcement made by President Cyril Ramaphosa regarding the official 21-day lockdown from Covid-19 global pandemic on 23 March 2020, 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. South African Reserve Bank estimated the 21-day lockdown to have a direct impact on the contraction of the economy at 2.6 per cent (Cronje & Omarjee, 2020).

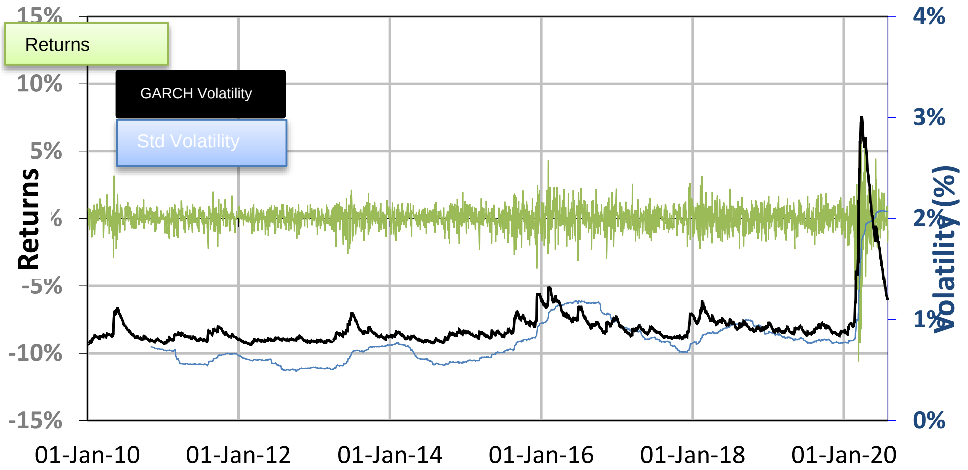

Figure 4.4. Variations of the General Autoregressive Conditional Heteroskedasticity (1, 1) and the Historical Standard Deviation for Mid-Cap Shares

Figure 4.5 illustrates a various volatility trend between GARCH (1, 1) and the historical standard deviation. In a similar manner as in Figure 4.4, the starting date for the historical standard deviation was on 1 November 2010 to capture the lost decade of the JSE. There was a distinct feature captured by the GARCH (1, 1) model that the historical standard deviation fell short from illustrating. It was a non-constant volatility which during high volatile periods the GARCH (1, 1) was able to demonstrate and those periods were 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 had an effect towards the economy (Cont, 2007). These large changes or share price spikes recorded on 20 May 2010, 06 May 2015, 11 December 2015, and 23 March 2020 drew in similar dates to those from the EWMA in Figure 4.4. The mid-cap share index was vulnerable to the negative consequences of load shedding. At least 59 billion and 118 billion rands had cost the South African economy in 2019 due to load shedding (Burkhardt, 2020).

Figure 4.5. Extreme Events for Mid-Cap Shares

Large changes in volatility clustering of share price return when clustered together as a result of extreme events, leave behind an economy that will take a long period to recover. Changes took into account to put the economy to its rightful place where foreign direct investments are prioritised and gdp is rising and the economy being in a good shape is an objective of every country to move forward. However, undergone extreme events seemed otherwise whereas their contribution to a falling economy had put a strain on monetary and fiscal policy makers (Ugwuanyi & Nwaocha, 2019).

The financial crisis of 2008 negatively affected mid-cap shares as they declined from 372 rands on 23 May 2007 to 217 rands on 27 October 2008. Extreme values for mid-cap shares amounted to 1.45 per cent and 1.53 per cent under the period 02 January 2007 to 31 July 2020. The percentage 1.53 was determined using the standard normal distribution. Meanwhile, the percentage 1.45 was determined using the 95 per cent confidence interval. Figure 4.7 and 4.9 featured volatility of mid-cap shares using the EWMA and GARCH (1, 1). A pattern of various extreme events was captured which further illustrated an inverse relationship between volatility and share price returns.

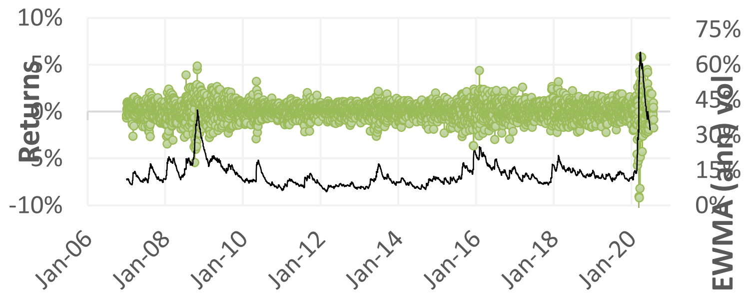

Figure 4.6. Extreme Values using the Exponentially Weighted Moving Average Model for Mid-Cap Shares

Share price return for the period 2 January 2007 to 31 July 2020 averaged negative 0.80 per cent whereas the EWMA volatility continued to showcase extreme events as discussed in Figure 4.6. The financial crisis of 2008/2009 share prices declined from a high of 300 rands on 18 March 2008 to 260 rands 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 share price returns on 23 March 2020 were reported at negative 8.23 per cent.

Annualised volatilities on 18 March 2008, and 11 December 2015, were at 20.2 per cent, and 22.4 per cent respectively when factoring 250 trading days in a year. Likewise, after the announcement of the 21 days lockdown to stop the spread of coronavirus Covid-19 on 23 March 2020, 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.

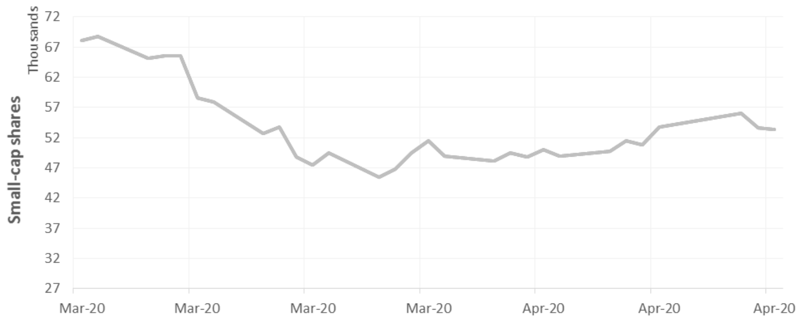

Figure 4.7. Mid-Cap Shares Movement during 21-day Lockdown in South Africa

The global unrest by Covid-19 was a major causation of the mid-cap share trend in the lockdown that was for 21 days as depicted in Figure 4.8. Mid-cap shares were at their highest on 6 March 2020 at 688 rands, which was the date before the official announcement of the lockdown. However, due to panic selling of shares by mid-cap share investors driven by fear, and overreacting to news surrounding the global pandemic, a downward trend of share prices followed whereby on 23 March 2020, share prices hit their lowest at 454 rands (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 the President Mr 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 starting day of the lockdown, shares declined to 490 rands. In addition, adhering to health guidelines and the industrial classification system which focused on industries that were eligible to resume operation and to what extend they were to function, the mid-cap share index was forward-looking (Truter, 2020).

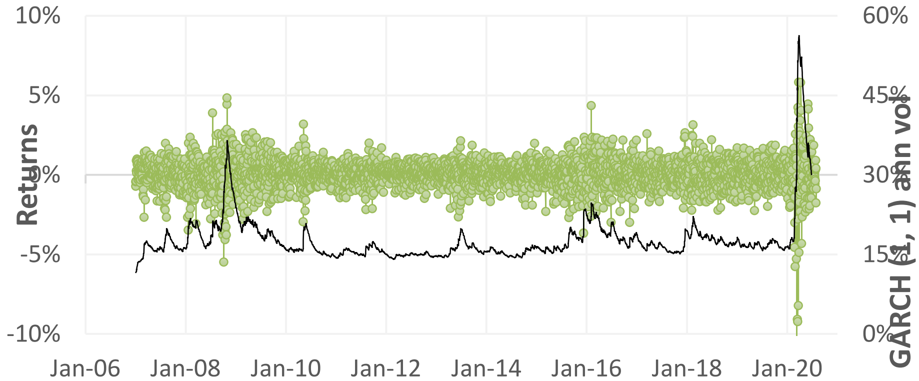

Figure 4.8. Extreme Values using the General Autoregressive Conditional Heteroskedasticity (1, 1) Model for Mid-Cap Shares

Annualised GARCH (1, 1) volatility for mid-cap shares depicted an inverse relationship with the share price returns in Figure 4.9. An average of the share price throughout the period 2 January 2007 and 31 July 2020 was at 546 rands. Whereas spikes in volatility were recorded in specific dates namely, 6 October 2008, 11 December 2015, and 23 March 2020 due to the 2008 financial crisis, the ongoing issue with Eskom load shedding, political climate, the downgrade South Africa's investment grade by Fitch to an unfavourable investment grade of negative BBB, and the Covid-19 global pandemic (Stanlib, 2017). The annualised volatilities in 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 based on 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 the GARCH (1, 1) respectively, given the encountered extreme events.

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 the following.

Firstly, 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 historical standard deviation was its limitation in capturing and recording extreme events. In addition, 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 for 31 July 2020. Including this value demonstrated the manner in which volatility was affected. Meanwhile, mid-cap shares overall risk of investment was lower than those of large and small-caps. This was based on the aspect that mid-cap shares were positioned to take advantage of small and large cap shares and viewed effective for long-term growth share investment.

Secondly, 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 during an extreme event, large changes in share price returns which shifted from positive to negative meanwhile, volatility shifted from negative to positive, depicted an inverse relationship between share price return and volatility. The model readjusted to a moderate movement in shares following extreme events and panic selling by investors as the magnitude of the extreme events was large. Extreme events which led to unfavourable share price returns, namely, heightened political risk and an indirect impact on share price returns – a downgrade of South Africa's sovereign credit rating on December 2015, discouraged foreign direct investment which was to contribute positively to an underperforming economy. Furthermore, following the announcement of the 21-day national lockdown on 23 March 2020 due to COVID-19, a global pandemic, it caused the highest volatility captured by both models – GARCH (1, 1) and EWMA, at a cost of returns in mid-cap shares. Volatility after the announcement of the lockdown was the highest in the period under analysis and signified the point of having a diversified investment portfolio and of that of the riskiness of investing in shares.

Thirdly, the historical standard deviation inability to capture volatility at a similar level as of the two models specifically during extreme events revealed its shortfall and disadvantaged investors for a holistic view and analysis of share price returns. The historical standard deviation did not track a similar volatility movement similar to that of the two models. This was based on the models optimal lambda which was used and respective equations that make up each model. The historical standard deviation as a measure of risk also adhered to the negative relationship of share price returns and volatility. However, solely using the historical standard deviation in volatility forecasting showed more of its shortfalls such as investors timing to sell shares when it was necessary for minimising losses that stemmed from extreme events.

Finally, the variations in the EWMA and GARCH (1, 1) models based on volatilities and their dominance in continuously updating forecasts subject to new information availability, and the quick rate of readjusting to effects of mid-cap share price shocks, influenced the decision of using the models instead of solely using the historical standard deviation. The most preferable model was based on an investors' ability to comprehend the costly use of the general autoregressive conditional heteroskedasticity for implementation, and processing large data. Additionally, the EWMA usage for its ability to minimise errors in volatility forecasting through considering previous errors in forecasting in which the accuracy was improved in the follow-up forecast. The decision was also based on the key weakness of the historical standard deviation of assigning the same weight in which the previous day's share price return had no effect on 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.

6. Recommendations

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

7. Limitations

Despite the unfavourable investment grade of negative BBB assigned by Fitch Ratings due to a weak economic performance and the outbreak of Covid-19 impact on mid-cap shares and optimal lambda that took place in the period under analysis, other extreme events that were not discussed on the basis of the South African mid-cap shares, proved to be the limitations of the study.

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