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STOCK MARKET VOLATILITY IN ZIMBABWE STOCK EXCHANGE DURING PANDEMIC PERIOD

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Abstract

Volatility is essential to consider uncertainty surrounding investments in financial assets. For this reason, financial industry regulators, mutual fund managers, individual and institutional investors, and policymakers are concerned about volatility. Against this background, this paper investigates the volatility of returns on the Zimbabwean stock market between January 2020 and January 2022. We use the All Shares Index for Zimbabwe Stock Exchange (ZSE) for volatility analysis and perform the quantitative investigation using GARCH family models. According to the AIC and SIC criterion, we use the GARCH (1,1) model and perform a complete analysis considering the results obtained from EGARCH (1,1) and IGARCH (1,1) regressions. Results report persistence in volatility, showing that it takes time for the market to digest information into the prices fully, and the shocks to conditional variance take longer to die out. Also, an asymmetry exists, implying that bad news and good news impact differently on the stock market, and the magnitude of volatility due to the good news is higher than bad news. Therefore, we conclude that positive news of the same magnitude impacts more than bad news. Investors rely more on the good news for effective decisions during the pandemic to earn more. Considering the results, any policy aimed at reducing the impact of the pandemic is favorable for investment.

Keywords: ASI, Black Swan, COVID-19, GARCH, Investment, Pandemic, Stock Market, Volatility, Zimbabwe

JEL Classifications: D81, E44, G11, G14, G15

1. Introduction

The world has witnessed one of the most significant pandemics in history that has spread across all nations. Though having started in November 2019 in China's Wuhan city, the World Health Organization (WHO) officially declared the coronavirus (COVID-19) outbreak a global pandemic on 11 March 2020. As Choi (2022) pointed out, the COVID-19 pandemic shock spread fast and broadly in the world economic market. The ongoing COVID-19 crisis is definitely the biggest of the twenty-first century yet experienced (Phadnis *et al.* 2021). The COVID-19 pandemic has various significant economic impacts. This shock wave has a possibility of badly affecting stock markets over the long term (Zhang *et al.* 2021). In particular, the pandemic severely affected worldwide financial markets (Ali *et al.* 2020; Goodell, 2020; Zhang *et al.* 2020; Gubareva, 2021; Zaremba *et al.* 2021). Stock markets are large financial entities that serve many purposes in their respective economies and the world at large (Bonga, 2014). The COVID-19 period has witnessed the fall of trade, tourism, aviation, and the transport industry, among other sectors. Economic activities were significantly limited as nations adopted strict quarantine policies (Rehman and Siddiqui, 2021). Travel restrictions, social distancing, lockdowns, and massive unemployment have struck economies, significantly impacting the financial markets (Yong *et al.* 2021).

During periods of pandemics, investors and markets encounter a high degree of uncertainty (Zhang *et al.* 2021). The rise in concern about extreme events, skewed towards worries about bad or disastrous events, may lead to increasing uncertainty (Bonga, 2019a). A higher degree of uncertainty can cause financial volatility, a measure of dispersion around the mean return of a financial asset (Bonga, 2014). As Bhatia and Gupta (2020) indicate, stock market volatility may be a composite of companies, industries, or the world over information that has been made public. In support, Alqaralleh and Canepa (2021) narrate that the COVID-19 outbreak triggered massive spikes in uncertainty in world financial markets.

For the operation of financial markets, volatility acts as a barometer of financial risk and financial uncertainty (Zhang *et al.* 2021), and it is widely used for asset pricing, hedging, portfolio selection, and many other fund investments-related businesses (Jegajeevan, 2012). According to Peiris and Peiris (2011), volatility disrupts capital markets, thus signaling the mispricing of stocks. In support, Yong *et al.* (2021, p. 191) narrate that "volatility plays an important role in portfolio selection, derivative pricing and risk management". As Magweva and Sibanda (2020) suggest, financial market volatility has increasingly become vital to investors and policymakers since the 2008 global financial crisis.

Financial markets volatility affects exchange rate movements. Using the portfolio balance approach, exchange rate movements are also determined by market mechanism (Cakan and Ejara, 2013; Farooq and Keung, 2004). The approach posits that causality on the relationship between stock prices and exchange rate runs from stock prices to exchange rate. A fall in stock prices maybe through slow economic growth would discourage flow of foreign investment, thus causing a fall in demand for the domestic currency and vice versa. Furthermore, a decrease in stock prices is associated with a depreciation while an increase is associated with an appreciation of the domestic currency.

Investors, financial analysts, and policymakers undertake modeling and forecasting of financial time series to enhance decision-making (Abdalla and Suliman, 2012). Volatile markets may erode investor confidence due to financial assets becoming less attractive because of erratic and wild movements of prices. Stock market investment is risky because one could lose all the invested capital (Zimbabwe Stock Exchange, 2019). Raising long-term capital may be very difficult and costly in financial markets with high volatility, leading to the misallocation of resources (Mashamba and Magweva, 2019). Volatility, however, is not directly observable but varies over time and is very sensitive to financial market variations (Awalludin *et al.* 2018).

This study aims to measure and estimate the Zimbabwean stock market volatility for the pandemic period using various generalized autoregressive conditional heteroscedasticity (GARCH) family models. Stock exchange in Zimbabwe dates back to 1896, with foreign participation enabled in 1993 and the current listing involving sixty-three equities. The study focuses on Zimbabwe because it is young in terms of development with several policies to boost

its recovery motive, henceforth a better target for investors. Studies are piling into the global village to explore how various stock markets behave during the crisis. The current study joins the research community by concentrating on the Zimbabwe stock market and contributing to literature for the pandemic and other crises alike if to pounce in the future. To our knowledge, this is the first study on COVID-19 and Zimbabwean stock market volatility based on a search in Google Scholar. Thus, the paper seeks to fill this gap.

A health crisis like the current pandemic can alter and change the nature of a stock return's volatility and hence has to be verified for investment decisions and policy. As Bhatia and Gupta (2020) argue, stock returns may have turned volatile due to panics brought by the pandemic stock, and the volatility may be country-specific. A study by Mahonye and Mandishara (2014) shows that both global and local economic factors determine stock market returns. Notably, many stock markets around the globe cratered as the coronavirus spread from China, with more effects on emerging markets and developing economies (Davis *et al.* 2021; Endri *et al.* 2021). The GARCH group of models appears to provide exact results (Zhang *et al.* 2021). Also worth noting is that GARCH models tend to fit the data frequency at hand (Zivot, 2009). The first volatility model is Autoregressive Conditional Heteroscedasticity (ARCH), created by Engle (1982). ARCH was expanded to GARCH by Bollerslev (1986), and more forms of GARCH models are in place to address some weaknesses of the first models and complement the analysis. The study contributes to the quickly growing literature (Onali, 2020) on the pandemic by analyzing how the COVID-19 pandemic and possibly other related issues of similar nature impact stock market volatility in Zimbabwe.

The remainder of the study is organized into four sections. We review the literature in Section 2 and discuss the research methodology in Section 3. We analyze in Section 4 and conclude the paper in Section 5.

2. Literature review

Times of crisis are linked to high levels of uncertainty. As supported by Wagner (2020), the stock market is the most uncertain of all financial markets. People in uncertain times react by reducing investment in assets that are risky, thereby further causing markets to be more bearish (Haldar and Sethi, 2021). Some current studies show that the COVID-19 pandemic increases financial market volatility and reduces investment (Ashraf, 2020; Goodell, 2020; Sansa, 2020; Sha and Sharma, 2020).

Theoretically, black swan theory, prospect theory, heuristic theory, regret avoidance concept and the efficient market hypothesis (EMH) have a pandemic period related facts on stock markets. Taleb (2001) notes that the black swan theory is linkable to sudden and unexpected events affecting the stock market and commerce. Black swan is used as a metaphor for very rare events (Peša and Brajković, 2016), and the main three criteria describing it are rarity, extreme impact, and retrospective explanation (Brunåker and Nordqvist, 2013). The emergence and unique nature of COVID-19 that swamped the world qualify to be explained by the black swan theory. Black swan events like COVID-19 are known to be highly unpredictable. During such times, economic experts lessen the adverse effects and encourage portfolio diversification (Zhang *et al.* 2021). The global financial crisis of 2008 is another event in the pre-COVID era that affected the world financial markets, which may have similar effects to the current pandemic era. As Guei *et al.* (2020) indicate, the global financial crisis affecting many nations shows the vulnerabilities of the global financial system. Phadnis *et al.* (2021) narrate that given the severity and recency of the global financial crisis, it offers important lessons to understand and counter the current pandemic.

Propounding the prospect theory, Kahneman and Tversky (1979) insist that investors set and decide the portfolio under risk. The behavior and anomalies of a risk-averse investor are at the center of the prospect theory. It explains the inverse relationship between risk and return. According to Zhang *et al.* (2021), prospect theory can explain the occurrence of the negative association between stock returns and pandemics. Tvede (2002) criticizes this theory, indicating that it shows natural human behavior when an investor is nearly underway to face risks, ambiguity,

and insecurity. Most people, as also observed by Riaz *et al.* (2020), are heavily prone to inevitabilities, thereby confining on perceived secure outcomes.

The heuristic theory is linked to the “rule of thumb” and posits that there always exists a manner in which decision-making is made simpler and easier in complex cases and uncertain conditions. Kahneman and Tversky (1979) suggest that the course of reducing complexities through probabilities of evaluation and simple judgments to forecast the values of investments form part of the heuristic theory. To address identified bias in the original theory, Waweru *et al.* (2008) add two factors as part of the heuristic theory: "overconfidence" and "gambler’s fallacy".

The regret avoidance concept refers to the collective psychology of investors, which posits that investors are reluctant to make any wrong decisions avoiding disappointment and regret (Bell, 1983; Loomes and Sugden, 1982). Dodonova and Khoroshilov (2005) apply this concept to asset pricing and predict the market's overreaction to various news in their study, and they conclude that the regret avoidance concept is useful in explaining excessive volatility in stock yields. Furthermore, Li *et al.* (2021) formulate a quadratic function based on the theory and allocate a smaller regret degree parameter to the equation. The authors indicate that investors tend to be more cautious and hence less likely to be impacted by emotion under the influence of the COVID-19.

The efficient market hypothesis (EMH) indicates that it is not possible for investors to gain in the financial market by engaging into historical analyses. According to the EMH, stocks are always priced correctly since stock prices fully reflect all the available information at any given time. A study by Henriksson (2021) for Nordic countries provides evidence that market efficiency, as explained by the EMH, cannot be distinguished for periods during and after the financial crisis. Pillai and Pillai (2021), use an event study methodology for market efficiency determination in India during the pandemic period and find that the markets are inefficient. The study results are not in line with the EMH as results indicate the possibility of numerous opportunities to make abnormal profits. However, as Malkiel (2011) clarifies, EMH does not necessarily mean that there is no existence of bubbles in asset prices or profound influences that impact returns and risk premiums resulting from environmental and behavioral factors. It is believed that bubble identification in advance by policymakers is highly unlikely.

From the empirical side, the great uncertainty of COVID-19 and its associated economic losses caused stock markets to become highly volatile and unpredictable. Thus, much research focuses on the association between the pandemic COVID-19 and the volatility of the financial market. Endri *et al.* (2021) examine stock prices' response to COVID-19 for Indonesia Stock Exchange. The study employs an event study approach and GARCH model for January 6, 2020 – March 16, 2020. The study findings indicate that abnormal returns react negatively to COVID-19, and volatility fluctuation is very wide during the pandemic. GARCH (1,2) model is utilized for assessing volatility and predicting abnormal stock returns. The study concludes that to face uncertainty and increased volatility conditions, several lines of risk management are required for stock portfolio management. The conditions open speculation opportunities as markets will be inefficient.

Yong *et al.* (2021) estimate the volatility of two Asian stock markets: Bursa Malaysia and Singapore Exchange. Daily indices closing prices between July 1, 2019, and August 31, 2020, are used, dividing the sample into pre-COVID-19 and COVID-19 periods. GARCH, GARCH-M, TGARCH, EGARCH, and PGARCH models are applied for each subsample, with the best model selected using the lowest Schwarz information criterion (SIC). Both stock market returns are found to be quite persistent, and the persistence decreases for both stock market returns during the pandemic period. The paper concludes that the COVID-19 pandemic altered the distributional properties of GARCH models.

A study on the Romanian stock market by Gherghina *et al.* (2021) investigates the volatility of daily returns for January 2020 - April 2021. GARCH (1,1) approach is used for the quantitative investigation. The conditional volatility shows visible evidence of volatility that changes over the explored period. Romanian equity market volatility increases in the first quarter of 2020 to a level almost similar to the one observed during the global financial crisis, and after

that, volatility has a downward trend. Using the vector auto-regression (VAR) model, no causal link is detected between the COVID-19 variables and the stock market index.

Kusumahadi and Permana (2021) examine the effect of COVID-19 on stock return volatility in 15 countries around the globe. High-frequency daily data from January 2019 to June 2020 is used. The study observes that exchange rate changes negatively impact stock returns in many countries. Structural changes are observed related to COVID-19. Relying on the TGARCH model, significant evidence exists about the impact of the COVID-19 pandemic on the stock return volatility in all nations examined except the United Kingdom.

A study by Baker *et al.* (2020) attempts to identify the impact of a current pandemic on stock market volatility. The study discovers that government limitations on commercial activity and consumer restrictions are chief causes for increased volatility. Zhang *et al.* (2021), concentrating on technologically advanced countries (U.S.A, China, Switzerland, Sweden, Netherlands, and United Kingdom), examine the effect of the COVID-19 pandemic on stock market risk using the TGARCH model. They obtain that global financial markets risk level has noticeably increased due to the pandemic. The study reveals that uncertainty brought by the pandemic and the linked economic damage make stock markets highly volatile.

Baret *et al.* (2020) discuss the effect of the COVID-19 pandemic on banks and financial markets. The study argues that COVID-19 has significant impacts because the world recently witnessed decreases in shares, oil, equity, and bonds prices.

Based on the theories and empirical literature reviewed, the study's motive is to evaluate stock market behavior during the pandemic. For this, we scrutinize the volatility of the Zimbabwe stock market.

3. Data and methodology

This section is divided into two parts: data and methodology. The data section explains the data and how it is obtained. The methodology subsection explains how the analysis is conducted to attain study objectives. The empirical econometric model and appropriability are mentioned and justified in the methodology part, including statistical tests and data transformations.

3.1. Data

Time series data, namely the All Shares Index (ASI) from the Zimbabwe Stock Exchange, is used to examine the stock return performance for the pandemic period. Data used by the study is obtained from the ZSE publications and the Reserve Bank of Zimbabwe publications and reports. The ZSE has eight recorded and published indices: ASI, Medium Cap, Small Cap, Top 10, Top 15, Top 25, Industrials, and Mining. The ASI comprises all registered companies on the stock exchange. Monthly indices of the ASI are converted to continuous compounding by taking the log differences. The study uses monthly historical data, which is low-frequency data. Low-frequency volatility models are competitive. Hence, low-frequency data can be utilized to estimate and predict volatility in stock markets (Lyócsa *et al.* 2021). The pandemic sample starts in January 2020 and ends in January 2022.

3.2. Methodology

Distributional properties of the data are first checked using common descriptive statistics (mean, standard deviation, skewness, kurtosis, and Jarque-Bera). Stationarity tests (augmented Dickey-Fuller (ADF) test) and heteroscedasticity tests (Lagrange multiplier (LM) test) are performed. An efficient estimation technique requires stock market returns to be stationary. The heteroscedasticity test checks for the presence of the autoregressive conditional heteroscedasticity (ARCH) effects in the residuals of the stock returns, thereby enabling the application of generalized autoregressive conditional heteroscedasticity (GARCH) family models. Failure to account for the presence of conditional heteroskedasticity results in misleading results

(Sokpo *et al.* 2017). When ARCH effects are ignored, there may be a loss of efficiency (Bonga, 2019b).

Many volatility studies favor using the GARCH model over the ARCH model. Engle (1995) states that the ARCH model resembles a moving average specification than an autoregression. Because of the ARCH's drawbacks, Bollerslev (1986) extends GARCH to include the lagged conditional variance terms as autoregressive terms. Also, GARCH uses fewer parameters to capture long-lagged effects, leading to improved and efficient estimates. Bollerslev *et al.* (1992) indicates that GARCH (1,1) model appears sufficient to describe the volatility evolution of stock-return series. However, the current study considers both symmetric and asymmetric models (GARCH, GARCH in Mean (GARCH-M), Integrated GARCH (IGARCH), Exponential GARCH (EGARCH), Power GARCH (PGARCH), and Threshold GARCH (TGARCH)) since the Zimbabwe Stock Exchange (ZSE) is not extensively researched. Appropriate tests, such as Akaike Information Criteria (AIC) and Schwarz Information criteria (SIC), are carried out to determine the best model to be applied. For each model, a post-estimation test for further ARCH effects is done using the ARCH-LM test to confirm its efficiency for policy.

4. Data analysis

A graphical presentation of the All Shares Index (ASI) is in Figure 1. On average, a rising trend in the ASI is observed, from the lowest value of 332.9 in January 2020 to the highest value of 12079.74 in January 2022. However, there are some periods of slight decline within the study period.

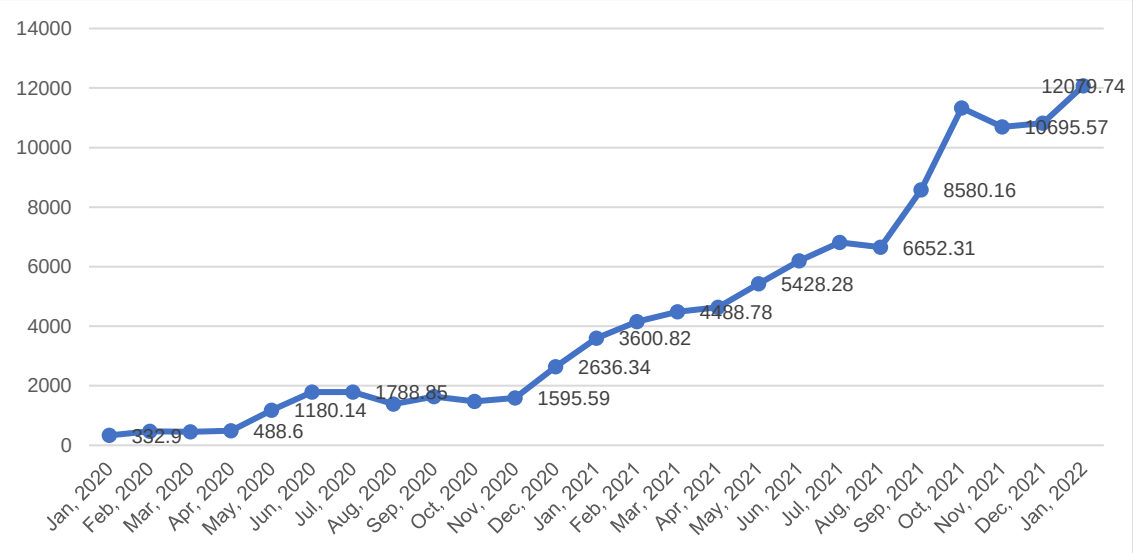

Figure 1. All Shares Index trend (January 2020-January 2022)
Source: Various ZSE and RBZ publications

Having gained confidence in stocks, investors may push prices further by purchasing stocks, and those invested in equity markets gain wealth. However, the rising prices may be linked to rising inflation. In this case, the real trend is necessary to reach a better conclusion as inflation in Zimbabwe has been increasing during the pandemic period. The stock market return is calculated from the ASI using the formula in Equation 1.

$$R_t = log(\frac{ASI_t}{ASI_{t-1}}) \quad (1)$$

, where R_t are the stock market returns at time t, ASI_t is the ASI at time t, $ASI_{t-1}$is the ASI at time $(t-1)$, and log is the logarithm.

Stock market returns are presented graphically in Figure 2. Volatility in returns with positive and negative values with different magnitudes is observed in Figure 2. No significant pattern is observable as a positive return is followed by a positive return or a negative return. Thus, no firm conclusions can be drawn from Figure 2 until a complete statistical analysis is made.

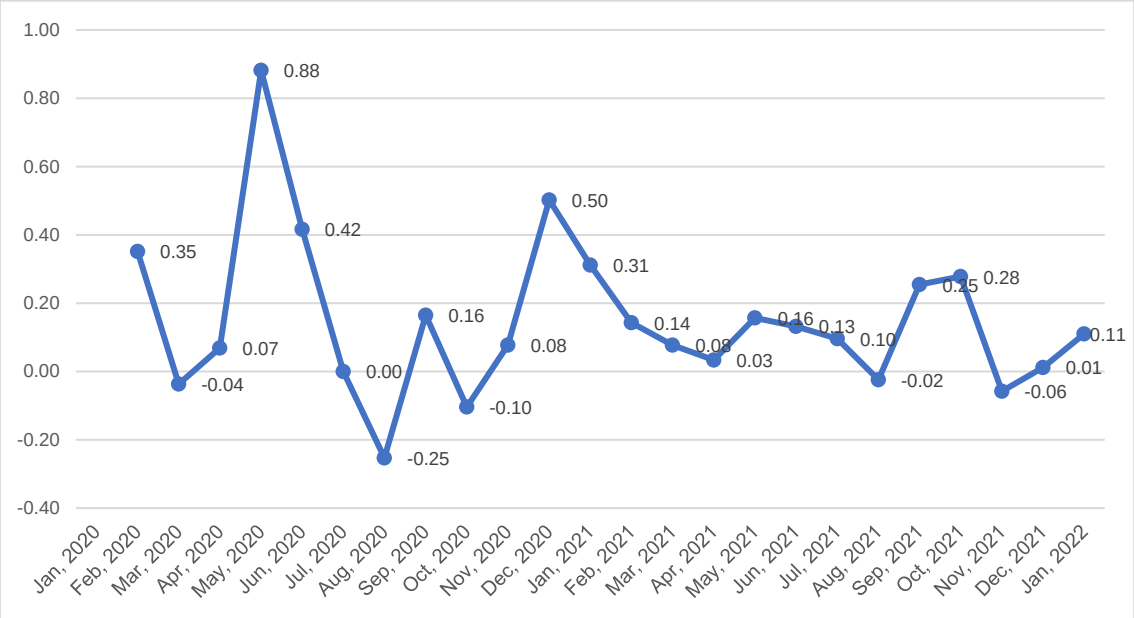

Figure 2. Stock market returns
Source: Various ZSE and RBZ publications

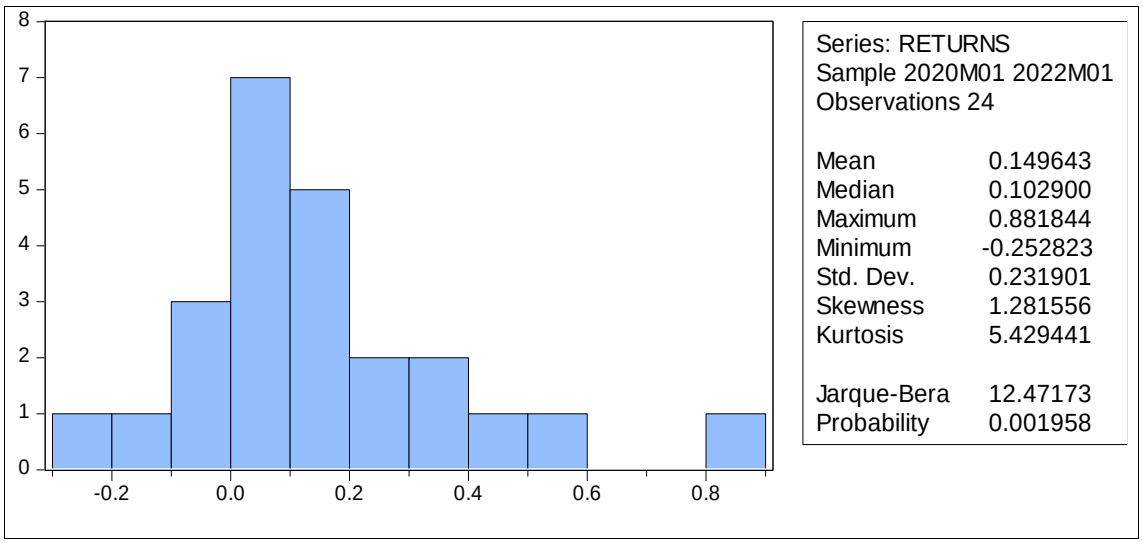

Figure 3. Summary statistics (stock market returns)
Source: Eviews Computations

The summary statistics, which provide critical information about volatility, are shown in Figure 3. The figure shows a positive mean return (0.149), indicating that the price increased over the period. The returns are positively skewed (1.282), showing a high probability of earning

returns less than the mean (0.149). The kurtosis (5.429) of the return series is higher than 3, which implies that the return series is fat-tailed and does not follow a normal distribution. This finding is in line with the study of Mashamba and Magweva (2019), which shows that the positive skewness noted in Zimbabwe means that the return distribution has a long right tail since large positive movements in stock prices are not usually matched by equally large negative movements. The Jarque-Bera test statistics (12.47) is significant at a 1% level (0.001958), confirming that the null hypothesis of normality is rejected. The stationarity test using the ADF test statistic is presented in Table 1.

Table 1. Stationarity test results

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-4.7876	0.0014***
Test critical values	1% level	-3.8315	
	5% level	-3.0300	
	10% level	-2.6552	

Note: *** denotes significance at a 1% level.

Source: Eviews output

The ADF statistic in Table 1 (-4.788) is less than the critical values (and the p-value is significant), indicating that the stock market return series is stationary. The statistical properties of the return series are not affected by time. The study worked with stationary data (no unit roots are detected), ensuring the derivation of reliable results for policy.

Next, ARCH effects are tested. With the help of the ACF and PACF, an ARIMA (1,1) model is estimated, and residuals (ε_t) are saved and squared to form a new variable (ε_t^2). The variance of the residuals is then calculated and saved as another new variable (δ_t^2). The model shown in Equation (2) is used for the ARCH-LM test.

$$\delta_t^2 = \varphi + \sum_{i=1}^{k} \beta_i \varepsilon_t^2 \tag{2}$$

, where φ, β_i, $i = 1$, and k are nonnegative constants. Using the ACF, the value of k is found to be equal to 2. The results for the estimation utilizing the Equation (2) and ARCH-LM heteroskedasticity test using q = 6, with the help of the correlogram, are presented in Table 2.

Table 2. Heteroskedasticity Test Results

Heteroskedasticity Test: ARCH			
F-statistic	4.104256	Prob. F(6,10)	0.0244
Obs*R-squared	12.09033	Prob. Chi-Square(6)	0.0600

Source: Eviews Output

The ARCH-LM test presented in Table 2 report a statistic of 0.0244 with a p-value of 0.06. The statistic is not significant at 1% and the rule of thumb 5%, however significant at the acceptable 10% (0.06). The test statistics is not highly significant, however, the null hypothesis of 'no arch effect' is rejected at 10% level, confirming the presence of ARCH effects in the residuals. The test statistics results warrant the study for the estimation of GARCH family models.

Results for the GARCH family models, which are GARCH (1,1) and GARCH-M (1,1), are presented in Table 3.

The estimated GARCH(1,1) model have insignificant AR and MA terms, though the ARCH and GARCH effects of the variance equation are significant at 10%. The model has proved not ideal, and the post-estimation test recorded an ARCH-LM statistic of 4.652, which is insignificant, indicating the presence of ARCH effects in the estimated model. Therefore, the model is not ideal. The obtained statistics ($\alpha + \beta$ = 0.51) is far less than 1. Thus, we conclude that there is no need for an IGARCH model. Using the same specification, the GARCH-M (1,1) model

also reports insignificant AR term, and a post-estimation test could not be carried out to assess the model.

Table 3. Regression results for GARCH (1,1) and GARCH-M (1,1)

		GARCH(1,1)	GARCH-M(1,1)
Mean Equation	Constant	0.1295*	-0.4337
	Risk Premium	-	-22.1655
	AR(1)	0.0109	-0.7181
	MA(1)	0.3746	3.0449***
Variance Equation	Constant	0.0189	0.0134*
	ARCH effect (α)	-0.0841*	-0.1127***
	GARCH effect (β)	0.5943*	0.1142***
	$\alpha + \beta$	0.5102	0.0014
Regression statistics	Log likelihood	8.1918	23.9609
	SIC	0.1119	-1.0698
	AIC	-0.1827	-1.4134
	ARCH-LM Statistic	4.6521	-
	Probability	0.0136	-

Note: ***, **, and * denote at 1%, 5%, and 10% significance levels, respectively.
Source: Eviews extraction

The EGARCH (1,1) also has insignificant AR and MA terms. The study modifies the model by dropping the AR and MA terms in its regressions. GARCH model, despite being a reasonably good model for financial time series analysis and conditional volatility estimation, in some cases has aspects of the model that require improvement so that it captures the characteristics and dynamics of a particular time series better (Zivot, 2009).

The results of the modified GARCH family models (after removing AR and MA terms in the mean equation) are presented in Table 4. Table 4 shows the regression results for the GARCH family models after removing the AR and MA terms, which are found insignificant in regressions presented in Table 1. The post estimation tests for all models using the ARCH-LM statistic show that after regressions, there exist no ARCH effects; hence results are reliable for policy. The constant coefficient of the mean equation is found significant at the 1% level for all the models.

The best model is determined for the financial time series data using the AIC and SIC criteria. The GARCH (1,1) models have the lowest AIC and SIC values, with -0.528903 and -0.332561, respectively. The study mainly relies on the results provided by the best model, which is the GARCH (1,1).

The constant term for the variance equation of the GARCH (1,1) model is significant and approximately equal to zero (0.001094), implying that current volatility is heavily premised on squared lagged residuals and previous stock return volatility. The ARCH and GARCH effects are significant at a 1% level, with values of -0.271503 and 1.26089, respectively. Combining the ARCH and GARCH effects ($\alpha + \beta$) gives the value of 0.989387, which is close to 1, indicating persistence in volatility and stronger ARCH and GARCH effects. Also, $\alpha + \beta$ does not exceed 1, indicating that the conditional variance process is not explosive.

High persistence observed from the GARCH (1,1) model may suggest that volatility might be non-stationary. As Zivot (2009) indicates, in such cases, the GARCH (1,1) model becomes the integrated IGARCH (1,1) model, which is a restricted version of the GARCH. The reported IGARCH (1,1) model parameters are all significant, with values of 0.209363 and 0.790653 for ARCH and GARCH terms, respectively. The GARCH term (0.790653) is positive and strongly significant at a 1% level, inferring that it takes time for the market to digest information into the prices fully, and the shocks to conditional variance take longer to die out. This result is not in line with the EMH hypothesis, which suggests that stocks are always priced correctly, and stock prices fully reflect all the available information at any given time.

Table 4. Regression results for GARCH family models

		GARCH(1,1)	GARCH-M(1,1)	EGARCH(1,1)	IGARCH	TGARCH(1,1)	PGARCH(1,1)
Mean Equation	Constant	0.1087***	0.4174***	0.1048***	0.1320***	0.1636***	0.0959***
	Risk Premium		-1.7250*				
Variance Equation	Constant	0.0011***	0.0519**			0.0201	
	ARCH effect	-0.2715***	-0.0578*		0.2094**	0.0299**	
	Asymmetric					-0.321251	
	GARCH effect	1.2609***	-0.3476		0.7906***	0.6111**	
	$\alpha + \beta$	0.9894	-0.4055				
	C(2) - Constant			-6.1674***			0.0036
	C(3) - ARCH			0.9447*			-0.3352***
	C(4)-Asymmetry			1.1643**			-0.5940
	C(5) - GARCH			-0.7506***			1.3025***
Regression Statistics	Log likelihood	10.3468	9.4767	7.1261	2.4626	5.5666	10.4623
	SIC	-0.3326	-0.1276	0.0683	0.0596	0.1982	-0.2098
	AIC	-0.5289	-0.3731	-0.1772	-0.0385	-0.0472	-0.4552
	ARCH-LM Stat.	0.2471	0.0015	0.4707	0.1573	0.1237	0.0373
	Probability	0.6243	0.9693	0.5002	0.6957	0.7285	0.8487

Note: ***, **, and * denote at 1%, 5%, and 10% significance levels, respectively.
Source: Eviews extraction

The GARCH (1,1) model, though found as the best model using AIC and SIC criteria, does not consider the leverage effects. The GARCH model is based on the assumption that positive and negative shocks equally impact the stock market. This weakness of the GARCH model is solved by considering the EGARCH model. The asymmetric coefficient of the EGARCH (1,1) is positive (1.164305) and significant at a 5% level, implying that the impact of good news and bad news of the same magnitude have a different impact on the stock market. More specifically, a coefficient of 1.164305 implies that positive news of the same magnitudes impact more than bad news on the stock market. This finding may be because the country is in the pandemic period, and every investor is more sensitive and eagerly waits for a better environment with the declining pandemic effects. With the pandemic in full swing in 2021, most investments hit a pause button, bringing down economic activity in the country and further driving the markets down. Although this is bad news for existing investors, it is good news for new investors because they could buy stocks at lower prices. The pandemic also allows investors to invest in alternative assets that are less affected by the uncertainties of the pandemic.

There is evidence of both positive and negative news about the pandemic increased volatility in the Zimbabwe stock market. News about the pandemic cause volatility in the stock market. Averagely, both good and bad news translate into increased activity in the stock market. Good news increase demand, while bad news increase the sell-off of shares by investors. However, the magnitude of volatility is high for good news and low for bad news. Our results are comparable to Alzyadat *et al.* (2021), who establish substantial evidence of the news effect of a health crisis on Saudi Arabia's stock market. Just like what Zhang *et al.* (2021) obtain for technologically advanced countries (U.S.A, China, Switzerland, Sweden, Netherlands, and United Kingdom), the current study reveals that uncertainty brought by the pandemic and the linked economic damage makes stock markets highly volatile. Furthermore, as Endri *et al.* (2021) observe for the Indonesia stock market, the current study finds that volatility fluctuation in the Zimbabwean stock market is extremely wide during the pandemic period.

5. Conclusion and policy recommendations

This study explored the volatility of the Zimbabwe stock market using monthly ASI data for the period January 2020 and January 2022. Symmetric and asymmetric GARCH models were both considered for the analysis after ARCH effects had been detected in the financial time series data. The study estimated the GARCH (1,1), GARCH-M (1,1), EGARCH (1,1), IGARCH (1,1), PGARCH, and TGARCH (1,1) models. Using the AIC and SIC, we determined that the GARCH

(1,1) is the best model. Additionally, the study considered regression results from the EGARCH model since GARCH does not address the asymmetric issue. Asymmetry was found significant, and the good news of the same magnitude was found to have a greater impact on the stock market than bad news. Such results were observed in other stock markets in countries like the U.S.A, China, Switzerland, Sweden, Netherlands, United Kingdom (Zhang *et al.* 2021), Indonesia (Endri *et al.* 2021), and Saudi Arabia (Alzyadat *et al.* 2021). The study results showed that for efficient investment to occur, investors required the investment climate to change for the better. Investors were more pushed by positive news than negative news in the market. Additionally, the current study results generally confirmed that the volatility of the Zimbabwe stock market was high during the pandemic period.

Although crises are often experienced globally, COVID-19 can be seen as a rare event, supported by the black swan theory. COVID-19 spread and its effect on stock markets is an investment concern, even when the heuristic theory posits that there always exists a manner in which decision-making is made simpler and easier in complex cases and uncertain conditions. As explained by the regret avoidance concept, investors remain unwilling to make any wrong decisions to avoid disappointment and regret. Whenever uncertainty is brought into the market by disasters, policymakers should work to reduce uncertainty through relevant policies to avoid prosperity disruption. Risk and uncertainty affect decision-making, even though the prospect theory insists that investors set and decide the portfolio under risk. Health policies should be executed during the pandemic to contain the spread of the deadly disease. Health is essential for human capital, which is an integral determinant of economic development. Appropriate macroeconomic policies should be the target to limit financial and economic losses. Through the central bank, the government should provide monetary policy accommodation in the economy so that ample liquidity is available to ensure the well-functioning of markets. During the crisis, governments should also protect and promote critical domestic industries, provide incentive schemes to industries that engage in health-related research and development, and enforce mandatory production of medical equipment to curtail the impact of the pandemic on the economy. However, the government's capabilities to design industrial strategies should continually be strengthened, even during times of no crisis. This study helps understand the mechanisms and hints at which government policies should be prioritized and implemented to contain the effects of the pandemic on the stock market. Zimbabwe should continue efforts to advance its capital market to strengthen its long-term resilience to the COVID-19-induced crisis and future similar calamities.

Future research might consider comparing the pre-pandemic and pandemic periods to explore the differences in volatility magnitudes. Also, extending the exploration to more countries, particularly within a regional concept, and studying disparities and resemblances would yield more insightful outcomes.

References

Abdalla, S. Z. S. and Suliman, Z., 2012. Modelling stock returns volatility: empirical evidence from Saudi Stock Exchange. *International Research Journal of Finance and Economics*, 85, pp. 166-179.

Ali, M., Alam, N., and Rizvi, S. A. R., 2020. Coronavirus (COVID-19)-an epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, 27, p. 100341. https://doi.org/10.1016/j.jbef.2020.100341

Alqaralleh, H. and Canepa, A., 2021. Evidence of stock market contagion during the COVID-19 pandemic: a wavelet-copula-GARCH approach. *Journal of Risk and Financial Management*, 14(7), p. 329. https://doi.org/10.3390/jrfm14070329

Alzyadat, J. A., Abuhommous, A. A., and Alqaralleh, H., 2021. Testing the conditional volatility of Saudi Arabia stock market: symmetric and asymmetric autoregressive conditional heteroskedasticity (Garch) approach. *Academy of Accounting and Financial Studies Journal*, 25(2), pp. 1-9.

Ashraf, B. N., 2020. Stock markets' reaction to COVID-19: cases or fatalities? *Research in International Business and Finance*, 54, p. 101249. https://doi.org/10.1016/j.ribaf.2020.101249

Awalludin, S. A., Ulfah, S., and Soro, S., 2018. Modeling the stock price returns volatility using GARCH (1,1) in some Indonesia stock prices. *Journal of Physics: Conference Series*, 948(1), p. 012068. https://doi.org/10.1088/1742-6596/948/1/012068

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., and Viratyosin, T., 2020. *The unprecedented stock market impact of COVID-19*. Working Paper No. 26945. Cambridge: National Bureau of Economic Research. https://doi.org/10.3386/w26945

Baret, S., Celner, A., O'Reilly, M., and Shilling, M., 2020. COVID-19 potential implications for the banking And capital markets sector. *Maintaining Business And Operational Resilience*, 2(2), pp. 96-108.

Bell, D. E., 1983. Risk premiums for decision regret. *Management Science*, 29(10), pp. 1156-1166. https://doi.org/10.1287/mnsc.29.10.1156

Bhatia, P. and Gupta, P., 2020. Sub-prime crisis or COVID-19: a comparative analysis of volatility in Indian banking sectoral indices. *FIIB Business Review*, 9(4), pp. 286-299. https://doi.org/10.1177/2319714520972210

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), pp. 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T., Chou, R. Y., and Kroner, K. F., 1992. ARCH modeling in finance: a review of the theory and empirical evidence. *Journal of Econometrics*, 52(1-2), pp. 5-59. https://doi.org/10.1016/0304-4076(92)90064-X

Bonga, W. G., 2014. Empirical analysis of stock returns and volatilityof the Zimbabwean stock markets. *IOSR Journal of Economics and Finance*, 5(6), pp. 46-57. https://doi.org/10.2139/ssrn.2400088

Bonga, W. G., 2019a. *Measuring macroeconomic uncertainty in Zimbabwe.* Paper No. 94759. Munich: MPRA. [online] Available at: <https://ssrn.com/abstract=3419976> [Accessed on 1 Marc 2022].

Bonga, W. G., 2019b. *Stock market volatility analysis using GARCH family models: evidence from Zimbabwe stock exchange*. Paper No. 94201. Munich: MPRA. [online] Available at: <https://ssrn.com/abstract=3402342> [Accessed on 1 March 2022].

Brunåker, F. and Nordqvist, A., 2013. *A Performance Evaluation of Black Swan Investments*. Student Essay. Gothenburg: University of Gothenburg. [online] Available at: <http://hdl.handle.net/2077/33388> [Accessed on 1 March 2022].

Cakan, E. and Ejara, D. D., 2013. On the relationship between exchange rates and stock prices: Evidence from emerging markets. *International Research Journal of Finance and Economics,* (111), pp. 115-124. [online] Available at: <https://ssrn.com/abstract=2343654> [Accessed on 1 March 2022].

Choi, S.-Y., 2022. Dynamic volatility spillovers between industries in the US stock market: Evidence from the COVID-19 pandemic and black monday. *The North American Journal of Economics and Finance*, 59, p. 101614. https://doi.org/10.1016/j.najef.2021.101614

Davis, S. J., Liu, D., and Sheng, X. S., 2021. Stock prices and economic activity in the time of coronavirus. *IMF Economic Review*, 70(1), pp. 32-67. https://doi.org/10.1057/s41308-021-00146-4

Dodonova, A. and Khoroshilov, Y., 2005. *Applications of regret theory to asset pricing*. [online] Available at: <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=301383> [Accessed on 1 March 2022].

Endri, E., Aipama, W., Razak, A., Sari, L., and Septiano, R., 2021. Stock price volatility during the COVID-19 pandemic: the GARCH model. *Investment Management and Financial Innovations*, 18(4), pp. 12-20. https://doi.org/10.21511/imfi.18(4).2021.02

Engle, R. F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 50(4), pp. 987-1007. https://doi.org/10.2307/1912773

Engle, R. F., 1995. *ARCH: Selected Readings (Advanced Texts in Econometrics)*. Oxford: Oxford University Press.

Farooq, M. T. and Keung, W. W., 2004. Linkage between stock market prices and exchange rate: a causality analysis for Pakistan. *The Pakistan Development Review*, *43*(4-II), pp. 639-649. https://doi.org/10.30541/v43i4iipp.639-649

Gherghina, Ș. C., Armeanu, D. Ș., and Joldeș, C. C., 2021. COVID-19 pandemic and Romanian stock market volatility: a GARCH approach. *Journal of Risk and Financial Management*, 14(341), pp. 1-29. https://doi.org/10.3390/jrfm14080341

Goodell, J. W., 2020. COVID-19 and finance: agendas for future research. *Finance Research Letters*, 35, pp. 1-5. https://doi.org/10.1016/j.frl.2020.101512

Gubareva, M., 2021. The impact of Covid-19 on liquidity of emerging market bonds. *Finance Research Letters*, 41, p. 101826. https://doi.org/10.1016/j.frl.2020.101826

Guei, K. M., Choga, I., and Rena, R., 2020. Predicting stock market volatility: a comparative performance study among BRICS countries. *Journal of International Economics*, 11(2), pp. 39-55. [online] Available at: <https://www.ipeindia.org/wp-content/uploads/2021/04/IPE-JoIE-Jul-Dec-2020-FINAL.pdf#page=43> [Accessed on 1 March 2022].

Haldar, A.,and Sethi, N., 2021. The news effect of COVID-19 on global financial market volatility. *Buletin of Monetary Economics and Banking*, 24, pp. 33-58. https://doi.org/10.21098/bemp.v24i0.1464

Henriksson, A., 2021. *Market Efficiency and the financial crisis: a study based on the market efficiency in the Nordic countries.* Unpublished Bachelor's Thesis. Växjö: Linnaeus University. [online] Available at: <http://urn.kb.se/resolve?urn=urn%3Anbn%3Ase%3Alnu%3Adiva-104589> [Accessed on 1 March 2022].

Jegajeevan, S., 2012. Return volatility and asymmetric news effect in Sri Lankan stock market. *Staff Studies, Central Bank of Sri Lanka*, 40(1-2), pp. 37-57. https://doi.org/10.4038/ss.v40i1.4680

Kahneman, D., and Tversky, A., 1979. Prospect theory: an analysis of decision under risk. *Econometrica*, 47(2), pp. 263-291. https://doi.org/10.2307/1914185

Kusumahadi, T. A. and Permana, F. C., 2021. Impact of COVID-19 on global stock market volatility. *Journal of Economic Integration*, *36*(1), pp. 20-45. https://doi.org/10.11130%2Fjei.2021.36.1.20

Li, Y., Luo, Y., and Zhou, Y., 2021. Empirical analysis of optimal stock portfolio under the background of COVID-19. E3S Web of Conferences, 235, p. 01027. https://doi.org/10.1051/e3sconf/202123501027

Loomes, G. and Sugden, R., 1982. Regret theory: an alternative theory of rational choice under uncertainty. *The Economic Journal*, 92(368), pp. 805-824. https://doi.org/10.2307/2232669

Lyócsa, Š., Plíhal, T., and Výrost, T., 2021. FX market volatility modelling: can we use low-frequency data? *Finance Research Letters*, 40, p. 101776. https://doi.org/10.1016/j.frl.2020.101776

Magweva, R. and Sibanda, M., 2020. Modeling and forecasting the volatility of returns in the infrastructure sector in emerging markets. *Eurasian Journal of Business and Economics*, *13*(25), pp. 37-52. https://doi.org/10.17015/ejbe.2020.025.03

Mahonye, N. and Mandishara, L., 2014. Stock market returns and hyperinflation in Zimbabwe. *Investment Management and Financial Innovations*, 11(4-1), pp. 223-232. [online] Available at: <https://www.businessperspectives.org/index.php/journals?controller=pdfview&task=download&item_id=6235> [Accessed on 1 March 2022].

Malkiel, B. G., 2011. The efficient-market hypothesis and the financial crisis. In *Rethinking Finance: Perspectives on the Crisis*. New York: Russel Sage Foundation. [online] Available at:

<https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.370.912&rep=rep1&type=pdf> [Accessed on 1 March 2022].

Mashamba, T. and Magweva, R., 2019. Dynamic volatility behaviour of stock markets in Southern Africa. *Journal of Economic and Financial Sciences*, 12(1), pp. 1-8. https://doi.org/10.4102/jef.v12i1.396

Onali, E., 2020. *Covid-19 and stock market volatility.* [online] Available at SSRN: <https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=3571453> [Accessed on 1 March 2022].

Peiris, T. U. I. and Peiris, T. S. G., 2011. Measuring stock market volatility in an emerging economy: empirical evidence from the Colombo stock exchange (CSE). In *International Research Conference, University of Kelaniya-Sri Lanka.*

Peša, A. R. and Brajković, A., 2016. Testing the 'black swan effect' on Croatian stock market between 2000 and 2013. *Emerging Markets Journal*, 6(1), pp. 1-16. https://doi.org/10.5195/emaj.2016.92

Phadnis, C., Joshi, S., and Sharma, D., 2021. A study of the effect of black swan events on stock markets - and developing a model for predicting and responding to them. *Australasian Accounting, Business and Finance Journal*, 15(1), pp. 113-140. https://doi.org/10.14453/aabfj.v15i1.8

Pillai, G. P. and Pillai, A., 2021. Efficient market hypothesis during the time of COVID. *International Journal of Recent Technology and Engineering*, 10(1), pp. 21-29. https://doi.org/10.35940/ijrte.a5667.0510121

Rehman, H. U. and Siddiqui, D. A., 2021. *COVID-19 and the financial markets' volatility and returns*. [online] Available at SSRN: <https://doi.org/10.2139/ssrn.3941990> [Accessed on 1 March 2022].

Riaz, S., Ahmed, R., Parkash, R., and Ahmad, M. J., 2020. Determinants of stock market investors' behaviour in COVID-19: a study on the Pakistan stock exchange. *International Journal of Disaster Recovery and Business Continuity*, 11(3), pp. 977-990. https://doi.org/31219/osf.io/4s9xe

Sansa, N. A., 2020. The impact of the COVID-19 on the financial markets: evidence from China and USA. *Electronic Research Journal of Social Sciences and Humanities*, *2*(II), pp. 29-39. https://doi.org/10.2139/ssrn.3567901

Sha, Y. and Sharma, S. S., 2020. Research on pandemics special issue of the journal emerging markets finance and trade. Emerging Markets Finance and Trade 56(10), pp. 2133-2137. https://doi.org/10.1080/1540496X.2020.1795467

Sokpo, T. J., Iorember, P. T., and Usar, T., 2017. Inflation and stock market returns volatility: evidence from the Nigerian stock exchange 1995Q1-2016Q4: an E-GARCH approach. *International Journal of Econometrics and Financial Management*, 5(2), pp. 69-76. https://doi.org/10.12691/ijefm-5-2-6

Taleb, A. A., 2001. The continuing behavioural modification of academics since the 1992 research assessment exercise. *Higher Education Review*, *33*(3), pp. 30-46.

Tvede, L., 2002. *The psychology of finance: understanding the behavioural dynamics of markets*. New Jersey: John Wiley & Sons.

Wagner, A. F., 2020. What the stock market tells us about the post-COVID-19 world. *Nature Human Behaviour*, 4(5), pp. 440-440. https://doi.org/10.1038/s41562-020-0869-y

Waweru, N. M., Munyoki, E., and Uliana, E., 2008. The effects of behavioural factors in investment decision-making: a survey of institutional investors operating at the Nairobi stock exchange. *International Journal of Business and Emerging Markets*, 1(1), pp. 24-41. https://doi.org/10.1504/ijbem.2008.019243

Yong, J. N. C., Ziaei, S. M., and Szulczyk, K. R., 2021. The impact of COVID-19 pandemic on stock market return volatility: evidence from Malaysia and Singapore. *Asian Economic and Financial Review*, 11(3), pp. 191-204. https://doi.org/10.18488/journal.aefr.2021.113.191.204

Zaremba, A., Aharon, D. Y., Demir, E., Kizys, R., and Zawadka, D., 2021. COVID-19, government policy responses, and stock market liquidity around the world: A note. *Research in*

International Business and Finance, 56, p. 101359. https://doi.org/10.1016/j.ribaf.2020.101359

Zhang, D., Hu, M., and Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*, p. 101528. https://doi.org/10.1016/j.frl-2020.101528

Zhang, N., Wang, A., Haq, N. U., and Nosheen, S., 2021. The impact of COVID-19 shocks on the volatility of stock markets in technologically advanced countries. *Economic Research-Ekonomska Istraživanja*, 35(1), pp. 2191-2216. https://doi.org/10.1080/1331677X.2021.1936112

Zimbabwe Stock Exchange, 2019. *ZSE investors guide. A guide to investing on the Zimbabwe Stock Exchange*. Harare: Zimbabwe Stock Exchange. [online] Available at: <https://www.zse.co.zw/wp-content/uploads/2019/12/ZSE-Investors-Guide.pdf> [Accessed on 1 March 2022].

Zivot, E., 2009. Practical issues in the analysis of univariate GARCH models. In T. Miskosch, J.-P. Kreiss, R. A. Davis, and T. G. Andersen, eds (2009). *Handbook of Financial Time Series.* Berlin: Springer, pp. 113-155. https://doi.org/10.1007/978-3-540-71297-8_5