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VOLATILITY PERSISTENCE IN INTERNATIONAL FINANCIAL MARKETS IN THE POST COVID-19 ERA

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ABSTRACT

The long-term behaviour of stock markets are of significant importance to asset managers and financial experts due to its direct link with security price valuation. Volatility persistence has a significant impact on the returns of security prices due to its time varying properties. However, there is no real meaningful effect of current volatility on future security prices and returns if the volatility is transitory and not persistent. The aim of this study was to explore conditional volatility properties and determine whether the current volatile environment would persist in the JSE, S&P 500, Nasdaq Index, SSE, CAC 40 and DAX markets. Using a GARCH 1.1 model and a Markov switching model, the findings revealed that volatility would persist in the JSE, S&P 500, Nasdaq Index, SSE, CAC 40, and the DAX from their ARCH and GARCH coefficients, as well as the delay parameters. In addition, the effects of past volatility in the Nasdaq, CAC 40, and DAX would remain in the forecast of variance. A diversified and broader investment approach should be used in the JSE, S&P 500, Nasdaq

Index, SSE, CAC 40, and DAX indexes to mitigate risk, and portfolio formation should not concentrate on any sector or asset classes.

Keywords: Volatility, financial markets, Covid-19, GARCH coefficient, ARCH term, conditional variance.

JEL Code: G1, G2, G4.

INTRODUCTION

Modelling volatility has always been an interesting phenomenon in finance and it is certainly an interesting time to investigate volatility persistence in financial markets because of the recent Covid-19 pandemic, which has had a mirage effect around the globe. Due to the introduction of the vaccine, financial markets are recovering from market disruptions caused by the Covid-19 pandemic (Shang, 2021). The spread of fear and uncertainty has created massive swings in market prices in almost all financial markets around the world. This was evident in stock markets like the S&P 500 index that had plummeted by over 30 percent at the beginning of 2020 with the spread of the pandemic (Li, 2020). The French Stock Market index (CAC 40) and the German blue chip companies trading on the Frankfurt Stock Exchange (DAX) fell by over 12 percent, which contributed to an overall 11 percent decrease in the value of European stocks at the beginning of February 2020, before increasing to a record high (Hathorn, 2021). Prior to the widespread impact of the virus, there was a significant jump in oil prices, breaking through the $1700 per ounce ceiling for the first time since 2012. However, the oil price tumbled to $250 per ounce in March 2020, losing about 60 percent of its value in the first quarter of 2020 due to the mismatch of demand fears and supply concerns (Camp et al., 2020). A similar situation was seen in the bond market, where nearly $4 trillion of municipal bonds experienced unprecedented volatility as investors sold off their positions amid concerns related to Covid-19 (Liang, 2020). The crisis produced unrivalled government responses, which included the introduction of extraordinary stimulus packages. There was a relaxation of banking regulations to ensure capital buffers were not impeding banks from supporting and stabilising economies. These actions were partly to curb financial market volatility and help ensure price stability.

The concept of volatility persistence refers to how today's volatility affects the conditional variance of future volatility (Wang & Yang, 2017). Therefore, today's unconditional volatility variance may be infinite and will continue in the future. Applying this definition in financial markets means that large or small volatility changes will tend to follow the same pattern in the future with unpredictable features and successive disturbances. The study of Karanasos et al. (2014) reveals that volatility has time varying properties with structural breaks. Muguto and Muzindutsi (2022) contend that volatility should not persist, because positive and negative news will induce an equal change. There has always been a compelling need for forecasting volatility persistence in financial markets as it determines the gains and losses from the erratic behaviour of financial markets. It can also be used to determine the level of risk involved in holding a security.

The aim of this study was to investigate the conditional volatility properties of the major financial markets around the world post the Covid-19 era. This study is significant to investment practitioners and market participants as it explores the extent to which the current volatile environment will persist, which has important implications for risk management and portfolio management. More specifically, knowledge of volatility persistence is important because the value of financial assets is directly linked to the level of volatility prevailing in the market; it denudes the linkage between some underlying risk factors and security price movements (Christiansen et al., 2012). Moreover, establishing the amount of risk to take should be based on the knowledge of the extent of volatility persistence in financial markets (Engle, 1982).

LITERATURE REVIEW

Theoretical Perspective

Heightened financial market volatility is a direct consequence of macro-economic uncertainty and a lack of liquidity (Kundu & Paul, 2022). These two economic forces are the main drivers of price fluctuations in financial markets. Macro-economic uncertainty makes it very difficult to price an asset, while a lack of liquidity causes fire sales where assets are traded at a lower price (Dow & Han, 2018). A clear distinction between realised and implied volatility should be made in the analysis and discussion of market volatility. Realised volatility is associated with technical analysis in which it is concerned with the past, and provides a vivid picture of historical asset price movements within a particular time frame (Paraschiv, 2020). Conversely, implied volatility describes expectations which are often used in option pricing and financial market trading (Mayhew, 1995). There exists a volatility gauge called the VIX index which is used by market participants and investors to access the level of risk and uncertainty in the market. In essence, the VIX is used to assess volatility expectations over a short period. High levels of uncertainty in the VIX index often results in fewer trading activities, a drop in liquidity, and a negative feedback loop. The three largest volatility spikes recorded in the VIX index were in 1987, 2008, and 2020, which was followed by reduced investor holdings.

Although volatility is usually analogous to bear markets, heightened financial market volatilities are also experienced in bull markets (Elgammal et al., 2021). This was evident in the 1990 dotcom boom where market volatility rose considerably alongside the tech stocks. The growth expectations that were placed on these untested tech stocks with the accompanying excitement gave rise to uncertainties, which had led to an unsustainable bubble growth. However, market volatility does find stability when market shock subsides and when market participants get a better understanding of the economic environment (Degiannakis et al., 2014).

Prior literature (Krichene, 2003; Bobeică & Bojeşteanu, 2008; Oh et al., 2008; Thupayagale, 2012; Gyamfi et al., 2016) contend that volatility tends to have a long-term memory due to recurring macro-economic cycles. These long-term memories are justified by hysteresis and repetitive irrational behaviour, which are contrary to the efficient market hypothesis (EMH). Irrational behaviours are captured in the heteroskedastic variance of the financial market (Maheu & McCurdy, 2000). Accordingly, modelling the heteroscedasticity behaviour and understanding the unconditional mean and variance of a security index is therefore, necessary for asset pricing, risk management, and portfolio optimisation. However, there are three underlying challenges in forecasting conditional volatility: (1) inferring a latent time series from a noisy observation and modelling non-linear temporal dynamics; (2) defining a positive symmetric covariance matrix; and (3) computing maximum likelihood estimations (Bauwens et al., 2006). Due to the aforementioned challenges, successfully quantifying the realised volatility does not necessarily lead to forecasting the implied volatility. Hence, the need arises for a more sophisticated model to capture the arbitrage effect between the realised and implied volatility. The Covid-19 pandemic has caused volatility spikes in the global financial markets. This certainly calls for concern as investors, market participants, and the general public are sceptical about the increasing risk as a result of volatility spikes. Although there are some risks worth taking, most risks are detrimental and should be avoided. For example, there is a risk when investing in a market where the economy is experiencing recession. Moreover, the question of the amount of risk to be taken should be analysed in conjunction with the concept of current and future volatilities. Volatility of idiosyncratic moves in stock markets will not be rewarded, as long as volatility persists (Visaltanachoti & Pukthuanthong-Le, 2009).

There are mainly two sources of volatility in stock markets, i.e., the amount of new information in the market, and macro-economic uncertainty. New information about certain events has a significant impact on stock prices. However, some information is important while others are not. New important information causes investors to change their expectations, which in turn affect the market price (Bookstaber & Pomerantz, 1989). This new information arrives in clusters and alters the way investors perceive the future. Macro-economic uncertainty is another factor that influences financial market volatility. Concerns about the macro-economic outlook contribute to financial market volatility because it is very difficult to price an asset in an uncertain environment. That is why investors are very interested in the macro-economic events associated with high volatility. According to Engle and Rangel (2006), the macro-economic factors that play an important role in driving financial market volatility include the following: high inflation, slow upward growth, recession and changes in short-term interest rates.

Volatility in the financial markets is still staggering because of the Russian-Ukraine crisis. Currently, financial markets are dominated by the Russian-Ukraine crisis, which has increased volatility and uncertainty in the financial system. The spill over effect is a decreased liquidity in certain markets, which prompt investment practitioners to shift their attention to active management. Commodity-based countries and countries with large amounts of United States denominated debt are experiencing tighter financial conditions. Russia is the third largest oil producer, accounting for 11 percent of the world's total supply (Carpenter, 2022). That is why the disruption caused by the Russian-

Ukraine war has significant consequences in the global supply of oil, as well as natural gas exports to the European Union.

Considering that financial markets are largely driven by market sentiments and are also emotionally structured, fear and panic tend to be reflected in stock prices (Ackert et al., 2003). Speculative and high growth stocks tend to be significantly affected by market volatility because fundamental drivers are driven by market sentiments. Future returns and the growth of speculative stocks take a downward turn with an increase in uncertainty, and investors tend to shift their sentiments toward risk-half. This means that they are less willing to take risks in the long and short term. Volatility in financial markets during Covid-19 has been extensively investigated during the pandemic. A summary of these studies are highlighted.

Table 1

Evidence of Market Volatility during the Covid-19 Pandemic

Study (Author & year of study)	Model	Period	Country	Findings
Topcu et al. (2021)	Lag augmented vector auto regression	3 January to 15 October, 2020	United States (US)	The fear and uncertainty of the pandemic triggered volatility across financial markets.
Endri et al. (2021)	GARCH model	2 March 2020 to 16 March 2020	Indonesia	Evidence of high volatility which had a negative impact on stock price returns on the Indonesian stock exchange.
Gherghina et al. (2021)	GARCH model	January 2020 to April 2021	Romania	Notable evidence of market volatility in the Bucharest Exchange Trading index which was similar to that of the 2008-2009 financial crisis.

(continued)

Study (Author & year of study)	Model	Period	Country	Findings
Ibrahim et al. (2020)	Continuous wavelet transformation analysis and plots and GJR-GARCH analysis	15 February to 30 May 2020	Asia-Pacific region	Financial markets in China, Japan, South Korea, Malaysia and Philippines experienced high volatilities during the Covid-19 pandemic, although government interventions help curb some of the volatility.
Mishra & Mishra (2020)	Fixed Effect and GARCH model	2 July 2019 to 12 June 2020	China, Hong Kong, India, Indonesia, Israel, Japan, Malaysia, Philippines, Singapore, South Korea, Thailand, and Taiwan	The Covid-19 pandemic amplified market volatility due to the impact of widespread fear.
Rahman et al. (2021)	Canonical correlation analysis	22 January 2020 to 31 December 2020	NASDAQ 100 options index, the S&P 500 and Dow Jones Industrial Average, DAX, CAC 40, and the EURO Stock 50 index	The announcement of new positive and death cases from the pandemic significantly increased market volatility.

Table 1 provides evidence of significant volatility during the Covid-19 pandemic. As has been well documented in the study of Muguto and Muzindutsi (2022), volatility can normalise in the future and cease to persist. Therefore, this study fills the gap in the literature by investigating the extent to which the current volatile environment will persist and in so doing, forecasts the implied volatility for selected financial markets. The next section highlights the blueprint used in the data analysis.

METHODOLOGY

To investigate volatility persistence, this study used a generalised autoregressive conditional heterosedasticity (GARCH) (1,1) model as proposed by Bollerslev (1986), and the Markov switching model developed by Hamilton (1989). In the GARCH (1,1) model, conditional volatility at time T is an autoregressive moving average (ARMA) relying on past volatilities and lagged values of the error term (Bauwens et al., 2006). In this respect, the GARCH model is very useful in investigating volatility persistence with lagged shocks together with its momentum. This model provides a parsimonious alternative to the higher autoregressive conditional heteroscedasticity (ARCH) model (Ruilova & Morettin, 2020). The GARCH (1,1) model has the following two important parameters; the ARCH term and GARCH coefficient. The ARCH term captures the extent to which the volatility changes over time due to the previous lag of autoregressive conditions, while the GARCH coefficient reveals the level of volatility symmetry in the market (Bollerslev, 1986). The sum of the ARCH and GARCH coefficients reveals the extent to which volatility will persist in the financial market. Volatility persistence is evident when the sum of the ARCH and GARCH term is closer than, or equal to 1 and vice versa (Nelson, 1990). The GARCH (1,1) model (Bollerslev, 1986) is given by the formula (1):

$$h_t = \alpha + \phi h_{t-1} + \beta\mu_{t-1}^2 \tag{1}$$

Where $h_{t=}$ Conditional variance

α = error term

ϕ = ARCH term

h_{t-1} = Lag value of Conditional variance

β = GARCH coefficient

μ_{t-1}^2 = Lag square error term

Despite the model's relevance, Malik et al. (2005) contend that in the absence of a regime shift, the GARCH (1, 1) model may overestimate volatility persistence. In order to have a robust finding, a Markov switching model has also been used to supplement the GARCH (1, 1) model. A Markov switching model is very useful in modelling the time-varying behaviour of volatility in financial markets (Mike et al., 1998). These time-varying behaviours of volatility may be subject to market shocks that create structural breaks (Ndako, 2012). In the context of this study, the Covid-19 pandemic may have caused market shocks that will affect the long memory in financial markets. The switching mechanism in the Markov model captures the complex volatility pattern by dating the breaking points, which is not possible in other models. Failure to incorporate these structural breaks can result in misspecifications. A Markov switching model for a given parameter Z_t is given in (2):

$$Z_t = \begin{Bmatrix} \alpha_0 + \beta_{z_{t-1}} + \varepsilon_t \\ \alpha_0 + \alpha_1 + \beta_{z_{t-1}} + \varepsilon_t \end{Bmatrix} \tag{2}$$

Where β_{z_t} and ε_t are mean zero random variables (Kuan, 2012). Most importantly the parameters ρ_{11} and ρ_{21} are the delay parameters in which their probabilities will also indicate whether the current volatility will persist, hence complementing the GARCH (1, 1) model.

The study used a sample of six major international financial markets, namely the Johannesburg stock exchange (JSE), the Standard and Poor 500 index (S&P 500), the Nasdaq Index, Shanghai Stock exchange (SSE), the French Stock Market index (CAC 40) and the German blue chip companies trading on the Frankfurt Stock Exchange (DAX). This is because these markets are among the largest financial markets in each continent around the world. The sample period was from January 1, 2020 to December 31, 2021, which was the crux of intense volatility in financial markets due to the Covid-19 pandemic.

RESULTS

Tables 2 and 3 present the results of the descriptive statistics and heteroscedasticity test, respectively. The R square values in Table 2 range from 1 percent to 19 percent in the financial markets under consideration. Most importantly, the Durbin-Watson statistics values are between 1.96 to 2.13, indicating the absence of autocorrelation (Kenton, 2021). The F-statistics p-values for the JSE, S&P 500, Nasdaq, CAC 40, and DAX, are significant at 5 percent, which indicate that the variance of the returns is not constant. This may signal the presence of volatility clustering. From Table 4, it can be seen that all conditions for the stability test are satisfied because the coefficients of the conditional variance are between 0 and 1, and the sum of the ARCH and GARCH coefficients is less than 1 (Bera & Higgins, 1993). The average return of the S&P 500 and Nasdaq index is positive and statistically significant at 5 percent. The past value of the Nasdaq is significant at 5 percent, meaning that the past returns in the Nasdaq can be used as a gauge for future returns. These results are also evident using the CAC 40 and DAX index with significant past value returns. The past value returns of the Nasdaq, CAC 40, and DAX have a very strong predictive ability because of the coefficients of their past value returns, and the ARCH term and GARCH term are all significant at 5 percent, which is congruent with the study of Nguyen et al. (2020).

Table 2

Descriptive Statistics

	R Square	Adjusted R Square	Mean Dependent Variable	Durbin-Watson Statistics
JSE	0.01	0.01	0.032%	2.02
S&P 500	0.08	0.08	0.025%	2.13
Nasdaq	0.19	0.19	0.029%	2.08
SSE	0.01	0.01	0.025%	1.96
CAC 40	0.04	0.04	0.025%	2.13
DAX	0.02	0.02	0.026%	2.07

Table 3

Heteroscedasticity Test: ARCH

	F-Statistics	p-value (F-Statistics)	p-value (Chi square-statistics)
JSE	3.05	0.0482*	0.0482*
S&P 500	22.95	0.000*	0.000*
Nasdaq	57.76	0.000*	0.000*
SSE	2.7	0.1006	0.1002
CAC 40	10.85	0.000*	0.000*
DAX	4.96	0.0073*	0.0075*

The results from Table 4 also indicate that volatility will persist in the JSE, S&P 500, Nasdaq Index, SSE, CAC 40 and the DAX, as the sum of their ARCH and GARCH coefficients are significant at 5 percent and close to 1. Table 4 also indicates that the decaying rate of volatility in the JSE, S&P 500, Nasdaq, SSE, CAC 40 and DAX are 0.02, 0.04, 0.04, 0.09, 0.05, and 0.03 respectively. Furthermore, the GARCH coefficients are greater than the ARCH coefficients, confirming that volatility will persist in all financial markets under consideration.

Table 4

GARCH (1.1) Results

	Average return	Value of past average return	ARCH coefficient	GARCH coefficient	Sum of ARCH and GARCH coefficient	Decaying rate of volatility (1-sum of ARCH & GARCH coefficient)
JSE	-0.0003 (0.71)	-0.028 (0.52)	0.05 (0.0001)*	0.93 (0.000)*	0.98	0.02
S&P 500	0.001 (0.00)*	0.02 (0.41)	0.27 (0.00)*	0.69 (0.00)*	0.96	0.04
Nasdaq	0.002 (0.007)*	-0.12 (0.02)*	0.19 (0.00)*	0.77 (0.00)*	0.96	0.04
SSE	0.01 (0.327)	0.01 (0.86)	0.19 (0.00)*	0.72 (0.00)*	0.91	0.09
CAC 40	0.001 (0.088)	-0.099 (0.04)*	0.19 (0.00)*	0.76 (0.00)*	0.95	0.05
DAX	0.001 (0.0815)	-0.109 (0.05)*	0.16 (0.00)*	0.81 (0.00)*	0.97	0.03

Note. *Significant at 5%

Regarding the Markov switching output in Table 5, sigma is significant in all financial markets for both regime 1 and regime 2. Moreover, the p-values of the delay parameters () are all significant at 5 percent, confirming the GARCH (1, 1) output results. The two robust findings confirm the persistence of volatility in the sample financial markets. As already documented in the studies by Ibrahim et al. (2020); Gherghina et al. (2021); Endri et al. (2021); Enow (2023); Rahman et al. (2021); and Topcu et al. (2021), markets will remain volatile with the arrival of positive and negative news.

Table 5

Markov Switching Model Results

JSE				
Variable	Coefficient	Standard Error	Z-statistics	P-value
		Regime 1		
C	0.001487	0.002638	0.563682	0.5730
Log(Sigma)	-3.577146	0.115888	-30.86714	0.0000*
		Regime 2		
C	-0.000538	0.000772	-0.696638	0.4860
Log(Sigma)	-4.439066	0.156048	-28.44678	0.0000*
		Transition Matrix Parameters		
ρ_{11}-C	1.441298	0.660442	2.182323	0.0291*
ρ_{21}-C	-2.498119	1.065777	-2.343942	0.0191*
S&P 500				
Variable	Coefficient	Standard Error	Z-statistics	P-value
		Regime 1		
C	0.001591	0.000444	3.579874	0.0003
Log(Sigma)	-4.694589	0.039875	-117.7320	0.0000*
		Regime 2		
C	-0.011364	0.008663	-1.311830	0.1896
Log(Sigma)	-2.794207	0.106898	-26.13894	0.0000*
		Transition Matrix Parameters		
ρ_{11}-C	4.560793	0.532895	8.558519	0.0000*
ρ_{21}-C	-2.475898	0.594259	-4.166362	0.0000*
Nasdaq				
Variable	Coefficient	Standard Error	Z-statistics	P-value
		Regime 1		
C	-0.002542	0.004119	-0.617204	0.5371
Log(Sigma)	-3.309863	0.090075	-36.74569	0.0000*
		Regime 2		
C	0.001989	0.000535	3.720936	0.0002
Log(Sigma)	-4.545140	0.039892	-113.9360	0.0000*
		Transition Matrix Parameters		
ρ_{11}-C	2.466291	0.472654	5.217963	0.0000*
ρ_{21}-C	-4.212685	0.476894	-8.833580	0.0000*

(continued)

SSE				
Variable	Coefficient	Standard Error	Z-statistics	P-value
		Regime 1		
C	-0.002288	0.002817	-0.812123	0.4167
Log(Sigma)	-3.842527	0.100703	-38.15694	0.0000*
		Regime 2		
C	0.000825	0.000429	1.925522	0.0542
Log(Sigma)	-4.793461	0.039309	-121.9440	0.0000*
		Transition Matrix Parameters		
ρ_{11}-C	2.258948	0.506996	4.455559	0.0000*
ρ_{21}-C	-4.201432	0.509416	-8.247548	0.0000*
CAC 40				
Variable	Coefficient	Standard Error	Z-statistics	P-value
		Regime 1		
C	-0.001	0.003	-0.359	0.720
Log(Sigma)	-3.517	0.074	-47.325	0.000*
		Regime 2		
C	0.001	0.000	1.911	0.056
Log(Sigma)	-4.737	0.041	-115.533	0.000*
		Transition Matrix Parameters		
ρ_{11}-C	3.106	0.539	5.768	0.000*
ρ_{21}-C	-4.550	0.562	-8.103	0.000*
DAX				
Variable	Coefficient	Standard Error	Z-statistics	P-value
		Regime 1		
C	-0.000763	0.002638	-0.289369	0.7723
Log(Sigma)	-3.553676	0.072844	-48.78471	0.0000*
		Regime 2		
C	0.000854	0.000463	1.843283	0.0653
Log(Sigma)	-4.737073	0.052580	-90.09305	0.0000*
		Transition Matrix Parameters		
ρ_{11}-C	2.708401	0.529242	5.117515	0.0000*
ρ_{21}-C	-3.958786	0.577152	-6.859174	0.0000*

Note. *Significant at 5%

CONCLUSION

Using the GARCH model, the aim of this study was to investigate the extent to which volatility will persist in the international financial world after the Covid-19 pandemic. The results indicate that volatility will persist in the financial markets under consideration. These findings are reliable because they appear to corroborate the results presented in Nguyen et al. (2022), the proposition that financial markets in developed countries have stronger long-term memory than less developed financial markets. In addition, the effects of past volatility in the Nasdaq, CAC 40, and DAX will remain in the forecast of variance due to the significant positive ARCH and GARCH coefficients. Moreover, a small number of market participants in the Nasdaq, CAC 40 and DAX may influence the stock price movements in either direction within a short period. As alluded to by Pereira and Zhang (2010), persistent volatility will affect the market volatility in the bond and equity markets. More specifically, one would expect to see a decrease in demand in the order-driven markets accompanied by wider bid-ask spreads. There might also be a decline in market depth in the sovereign bond markets. The number of corporate credit instruments may not match the corresponding increase in trading volume, which will increase the cost of providing liquidity. Investors and market participants should focus on a diversified investment approach in this market so that risks are not concentrated on any one sector or asset class. Additionally, a broader strategy of executing trade is highly recommended because financial markets will experience an increase in irrational behaviour because of a lack of confidence in the market. In short, financial markets are experiencing metastasis and therefore, market participants and investors should expect agitations, as well as persistent and volatile financial markets (Mohamed, 2022).

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