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Forecasting Volatility Persistence: Evidence from International Stock Markets

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Abstract: Volatility persistence represents a notable feature of financial markets and is a widely studied phenomenon that explores the clustering and leverage effects of stock market returns. Recognizing and incorporating volatility persistence into risk management, asset pricing, and portfolio management strategies provide valuable insights for market participants enabling them to navigate and capitalize on the dynamics of market volatility. The aim of this study was to empirically investigate whether the current high volatility in stock markets are temporal or will persist in the future. An ARCH model and a GARCH model were employed to achieve the aim of this study for the JSE, CAC 40, DAX, Nasdaq and Nikkei 225 from May 29, 2023 to May 29, 2018. The findings revealed that stock market volatility will persist at least for some time from the ARCH and GARCH output results. Active traders and market makers need to adapt their strategies in response to the expected volatility persistence. Higher levels of persistence may call for adjustments such as widening stop-loss orders to accommodate larger price swings or using more extended timeframes to capture sustained trends. Portfolio managers may also opt for strategies that thrive in volatile market conditions such as breakout trading or mean reversion strategies.

Keywords: Volatility Persistence; Stock Markets; ARCH model; GARCH model; Market efficiency

INTRODUCTION

Stock market volatility is a well-established phenomenon that has been studied extensively by academics, financial analysts and investors (Baek, Mohanty & Glambosky, 2020; Magner, Lavin,Valle & Hardy, 2021; Enow, 2022). While volatility can create both opportunities and risks for investors, it is important to have a critical perspective on its implications especially in the context of persistence. Volatility persistence is also a captivating and extensively studied phenomenon in stock markets that has garnered significant attention from researchers, practitioners, and policymakers alike. It refers to the tendency of stock market volatility to exhibit clustering or persistence over time (Godfrey & Agwu, 2018). This persistence is observed in the form of prolonged periods of high volatility followed by extended periods of relative calm (Gil-Alana, Infante & Martín-Valmayor, 2023).

Understanding volatility persistence is crucial for comprehending the dynamics of financial markets, estimating risk accurately and making informed investment decisions (Chaudhary, Bakhshi & Gupta, 2020). The study of volatility persistence in stock markets has been driven by two primary objectives (Hung, 2019). First, researchers aim to empirically establish the existence and magnitude of volatility clustering in stock returns (Enow, 2023). Second, they seek to identify the underlying causes and mechanisms that give rise to this persistence. By examining the empirical evidence and exploring theoretical explanations, scholars have made significant strides in shedding light on this intriguing phenomenon. Empirical evidence consistently supports the presence of volatility persistence in stock markets (Kaur, Jaisinghani & Ramalingam, 2019). Numerous studies have shown that during periods of high volatility, stock returns tend to cluster together forming distinct episodes of market turbulence (Shim, Kim & Choi, 2020). Likewise, periods of low volatility also exhibit lower clustering indicating the persistence of relative market calmness.

These empirical findings have been robust across various stock exchanges and time periods indicating the presence of a universal characteristic of stock market dynamics. There are many theoretical explanations proposed to elucidate the drivers of volatility persistence. One influential explanation is the leverage effect, which suggests that negative shocks to stock returns lead to increased future volatility (Zarafat, Liebhardt & Eratalay, 2022). This effect arises from the fact that firms' liabilities typically remain fixed, while their asset values decline during market downturns. Another explanation revolves around the heterogeneous nature of market participants. Different investors have varying investment horizons, risk preferences, and trading strategies.

The interaction between these heterogeneous agents can create feedback loops and amplification mechanisms, contributing to the persistence of volatility (Wehrli & Sornette, 2022). Considering these theoretical explanations of volatility persistence and the current economic climate, this study seeks to answer the following questions; Are there empirical evidence of volatility clustering in financial markets? Is there any evidence of leverage effects in stock market returns? Is there sufficient evidence to suggest that volatility will persist in the future? Understanding volatility persistence in stock markets has significant implications for various market participants. Risk managers rely on accurate volatility forecasts to estimate Value-at-Risk (VaR) and develop effective risk management strategies. By acknowledging the clustering nature of volatility, they can better prepare for periods of heightened market uncertainty and adjust risk mitigation measures accordingly.

Furthermore, volatility persistence challenges traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM), as it violates the assumption of independently and identically distributed returns. Incorporating volatility persistence into asset pricing models can enhance their accuracy and reflect the real dynamics of stock returns. Hence this study makes a noteworthy contribution by advancing the frontier of stock market volatility. The next section highlights the literature review followed by the methodology, the results, discussion and conclusion.

LITERATURE REVIEW

Volatility persistence is a crucial phenomenon to analyze in stock markets as it provides insights into the dynamics of market uncertainty and risk (Alotaibi, & Morales, 2022). Numerous empirical studies have consistently found evidence of volatility persistence in stock markets (Baek, Mohanty & Glambosky, 2020; Magner, Lavin,Valle & Hardy, 2021; Enow, 2023). These studies have examined various stock exchanges and time periods, providing robust evidence of clustering volatility patterns. The study of Shim, Kim, and Choi (2020) revealed that stock market returns tend to cluster together and periods of high volatility tend to lead to higher future volatility, forming distinct episodes of market turbulence. One key aspect of analyzing volatility persistence is the consideration of different time horizons. While short-term persistence is widely documented (Baur & Dimpfl, 2019), the extent of persistence in longer time frames remains a subject of debate.

Some studies (Malik, Ewing & Payne, 2005) have suggested that volatility persistence may weaken or even disappear in longer time horizons. This implies that the clustering of volatility might be more prevalent in the short run than in the long run. However, it is important to note that the specific time horizon and methodology used in the analysis can influence the findings. Different estimation techniques, such as rolling windows or long-memory models, may yield varying results, highlighting the importance of careful methodology selection. It is important to note that investors and portfolio managers need to consider volatility persistence when making portfolio allocation decisions. The recognition of clustering volatility patterns allows investors to tactically adjust their portfolio weights to capitalize on periods of high volatility and potentially benefit from increased trading opportunities. Strategies such as volatility targeting, which dynamically allocate portfolio assets based on current volatility levels, can help manage risk and potentially enhance returns (Kaczmarek, Będowska-S´ojka, Grobelny & Perez, 2022). Accordingly, volatility persistence is not a deterministic phenomenon as its characteristics can vary across different time periods, market conditions, and asset classes. Therefore, it is crucial to exercise caution and supplement the analysis of volatility persistence with other relevant factors and indicators to make well-informed investment decisions.

Volatility persistence in stock markets is a captivating and extensively researched topic. Empirical evidence supports the presence of clustering volatility patterns while theoretical explanations provide insights into the underlying mechanisms. The understanding of volatility persistence has important implications for risk management, asset pricing, and portfolio allocation decisions, allowing market participants to navigate the complexities of stock market dynamics more effectively. One of the main adverse implication of stock market volatility is that it can create instability in financial markets and the broader economy (Jin, 2017). When prices fluctuate wildly, it can lead to a loss of investor confidence and a decrease in the availability of credit and capital which can have negative impacts on businesses and individuals. Volatility persistence can also lead to mispricing of assets and inefficient allocation of capital (Enow, 2023).

When prices are highly volatile, it can be difficult for investors to accurately value assets and make informed investment decisions leading to the misallocation of resources which can have negative impacts on economic growth and productivity. When stock prices are highly volatile, it can be difficult for individual investors to compete with large institutional investors who have access to more information and resources. This can create a barrier to entry for small market traders and limit their ability to participate in the stock market. There are several factors that may contribute to volatility in stock market returns, these includes:

Economic indicators: Economic indicators such as GDP growth, inflation, and employment data can have a significant impact on stock market returns. Changes in these indicators can cause investors to reassess their expectations about the future direction of the economy and adjust their investment strategies accordingly.

Company-specific news: News related to specific companies, such as earnings reports or mergers and acquisitions, can also drive volatility in stock market returns. Positive news may lead to an increase in stock prices and lower volatility, while negative news can lead to a decrease in stock prices and higher volatility.

Geopolitical events: Geopolitical events such as wars, political unrest, or changes in government policies can also cause volatility in stock market returns. These events can create uncertainty and affect investor sentiment, leading to changes in stock prices and volatility.

Interest rates and monetary policy: Changes in interest rates or monetary policy decisions made by central banks can also have a significant impact on stock market returns. An increase in interest rates can make borrowing more expensive and slow down economic growth, leading to lower stock prices and higher volatility.

Investor sentiment: Investor sentiment can also be a major driver of volatility in stock market returns. When investors are optimistic about the future direction of the market, they may be more willing to take risks and invest in stocks, leading to lower volatility. Conversely, when investors are pessimistic, they may be more likely to sell their stocks, leading to higher volatility.

From the abovementioned factors that contributes to stock market volatility, it may be suggested that international stock exchanges may experience increasing volatility considering the continuous heightened inflation, high unemployment data results, political unrest and poor investor sentiments. However, it is necessary to ascertain these theoretical claims with empirical findings. This study therefore seeks to provide the empirical analysis to supplements the theoretical perspective of expected stock market volatility. The next section which is the methodology presents the blueprint of the study.

METHODOLOGY

Empirical analyses of volatility persistence typically involves the use of statistical methods to analyze historical price data and identify patterns or trends in volatility. The most intuitive measures involve the use of autoregressive conditional heteroskedasticity (ARCH) models and generalized autoregressive conditional heteroskedasticity (GARCH) models. ARCH and GARCH models are widely used to analyze and forecast volatility in financial time series data (Engle, 2001). This is because these models can capture the persistence and clustering effect of stock returns making them valuable tools for risk management, asset pricing, and portfolio allocation decisions. The ARCH model was introduced by Engle (1982) to explicitly account for time-varying volatility. The ARCH model assume that the conditional variance of a financial time series is a function of its past squared residuals, in other words, the current volatility is a function of past volatility and past squared errors (Engle, 1982). This allows the ARCH model to capture the clustering of volatility as high volatility periods are followed by subsequent periods of high volatility and vice versa.

The GARCH model introduced by Bollerslev (1986), extend the ARCH framework by incorporating lagged conditional variances as additional explanatory variables. The GARCH model allows for a more flexible and accurate representation of volatility dynamics. By including lagged conditional variances, GARCH models capture the persistence of volatility even more effectively (Bollerslev, 1986). These models also allow for the estimation of the impact of both past squared residuals and past conditional variances on current volatility. Both ARCH and GARCH models have been extensively used in empirical finance to examine volatility persistence and forecast future volatility where they estimate the parameters of volatility using maximum likelihood estimation (Raheem, Alhusseini & Alshaybawee, 2022). Once the parameters are estimated, volatility forecasts can be generated enabling market participants to make informed decisions regarding risk management, trading strategies, and asset allocation. One of the advantages of ARCH and GARCH models is their ability to capture the time-varying nature of volatility. They recognize that volatility is not constant but changes over time, and that past volatility levels influence future volatility. This feature is particularly important in financial markets, where volatility clusters during periods of market turmoil and subsides during calmer periods. The mathematical expressions of the ARCH and GARCH model is presented below;

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

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 (Bollerslev, 1986). Accordingly, volatility in financial markets will persist if the coefficients in the ARCH and GARCH models are significant and their sum close to 1 due to clustering and leverage effect. The main data that was used in this study was daily share price for the Johannesburg stock exchange (JSE), the French Stock Market index (CAC 40) and the German blue chip companies trading on the Frankfurt Stock Exchange (DAX), the Nasdaq Index and Tokyo Stock exchange (Nikkei 225). The Sample period was from May 29, 2023 to May 29, 2018 as it represents the most recent financial data. The section below presents the results and discussion section.

RESULTS AND DISCUSSION

The output of the data analysed using the ARCH and GARCH model is presented below.

Table 1: Descriptive statistics

	Mean	Standard Error	Standard Deviation	Variance	Kurtosis	Skewness	Range
CAC 40	0.031%	0.036%	1.300%	0.017%	11.75	-74.39%	20.67%
DAX	0.026%	0.038%	1.341%	0.018%	11.93	-39.95%	23.21%
JSE	-0.043%	0.048%	1.686%	0.028%	3.22	-25.81%	15.79%
Nasdaq	0.058%	0.046%	1.619%	0.026%	6.14	-39.58%	21.67%
Nikkei 225	0.033%	0.035%	1.238%	0.015%	3.69	4.35%	14.12%

Source: Author

Table 1 presents the results of the descriptive statistics output for a data analysis. The lower standard error values indicate that the sample period is an adequate representation of the population parameter. The range of the average returns for the sampled financial markets are within the 15.79% to 23.21% threshold which indicates that there may be no outliers. The standard deviation for all the sampled financial markets were very similar within a range of 1.2% to 1.68%. A similar observation was gleaned from the variance where the highest stock market variation was in the JSE. Almost all the returns were negatively skewed except the Nikkei 225 which had a positive skewness. By implication from the descriptive statistics, investors can expect frequent small gains and losses in the CAC 40, DAX, JSE and Nasdaq. Hence, investing in these markets may result in stable profits except the Nikkei 225. The ARCH and GRACH findings are highlights below.

Table 3: ARCH and GARCH results

Stock market	Value of past average return	ARCH coefficient	GARCH coefficient	ARCH and GARCH coefficient
CAC 40	-0.0193 (0.50)	0.1852 (0.000)*	0.757 (0.000)*	0.9422
DAX	-0.05 (0.10)	0.147 (0.000)*	0.803 (0.000)*	0.95
JSE	-0.119 (0.000)*	0.046 (0.000)*	0.891 (0.000)*	0.937
Nasdaq	-0.068 (0.022)*	0.157 (0.000)*	0.83 (0.000)*	0.987
Nikkei 225	-0.027 (0.38)	0.114 (0.000)*	0.806 (0.000)*	0.92

From Table 2, the conditions for the stability test are met as the sum of the ARCH and GARCH coefficients are less than 1 (Bera & Higgins, 1993). Also, the past returns for the JSE and Nasdaq can be reliably used as forecasts for expected returns because their p-values are less than 5%. Table 2 also suggests evidence of clustering and leverage effect for the CAC 40, DAX, JSE, Nasdaq, and Nikkei 225 because the ARCH and GARCH coefficients are all significant at 5% and their sum close to 1. The findings further revealed a decaying volatility rate in the CAC 40, DAX, JSE, Nasdaq, and Nikkei 225 which is 0.057, 0.05, 0.04, 0.063, 0.013, and 0.08, respectively. Therefore, it is evident from these results that volatility will persist in the sampled financial markets. By implications, higher expected volatility implies increased uncertainty and potential for larger price movements which can impact portfolio performance. Also, options with longer time to expiration may require higher premiums since there is a higher likelihood of significant price movements. Traders and investors pricing options should consider the potential impact of volatility persistence on option values. Executing larger position sizes may be riskier as they are more exposed to potential price swings. These persistent volatilities can create trends and price movements that can be capitalized upon through various trading strategies.

CONCLUSION

Volatility persistence has far-reaching implications across various areas of finance. It influences risk management practices, asset pricing models, portfolio allocation decisions, trading strategies, and financial market regulations. Recognizing and incorporating volatility persistence into decision-making processes provides market participants with valuable insights to navigate the complexities of financial markets and manage risk effectively. The aim of this study was to explore the extent to which the current volatile markets will persist in the future. The findings revealed that stock market volatility will persist at least for some time from the ARCH and GARCH output results. Therefore, active traders and market makers need to adapt their strategies in response to volatility persistence. Higher levels of persistence may call for adjustments such as widening stop-loss orders to accommodate larger price swings or using more extended timeframes to capture sustained trends. Portfolio managers may also opt for strategies that thrive in volatile market conditions, such as breakout trading or mean reversion strategies. Furthermore, active market participants can utilize volatility-related trading instruments, such as options and volatility exchange-traded products to directly speculate or hedge against future volatility levels. Options strategies like straddles or strangles may also benefit market participants from anticipated increases in volatility and exposure to losses.

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