Exploring Volatility Clustering Financial Markets and Its Implication

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ABSTRACT

Volatility clustering is a prominent feature of financial markets exhibiting persistent fluctuations in volatility over time. Its characteristics such as long memory, asymmetry and varying cluster durations pose challenges for market participants although it may also present some opportunities. The aim of this study was to investigate the historical patterns and statistical properties of volatility clustering across different financial markets. This study used a GARCH and ARCH model for four stock markets from June 14, 2018 to June 14, 2023. The findings revealed the presence of volatility clustering in line with prior study. These clustering which may be due to the recent episodes in financial markets such as the covid-19 poses significant risk for traders and active market participants. Hence, regulatory authorities need to implement measures to enhance market resilience, sufficient liquidity and regulate high-frequency trading activities to mitigate systemic risk.

Keywords: Volatility Clustering, GARCH Model, ARCH Model, Financial Markets.

1. INTRODUCTION

Volatility clustering is a phenomenon observed in financial markets where periods of high volatility tend to be followed by periods of high volatility and low volatility is followed by low volatility (Nguyen et al. 2020). This pattern of clustered volatility fluctuations has been extensively studied and has significant implications for asset pricing and portfolio management (Ruilova & Morettin, 2020; Ibrahim et al., 2020; Endri, 2021). Numerous studies have provided robust empirical evidence of volatility clustering across various financial markets where researchers have examined stock returns, exchange rates, commodity prices and other financial assets to uncover the presence of this phenomenon. One of the early studies of this concept by Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model to capture the persistence of volatility. Subsequent Bollerslev (1986) advanced the model by introducing the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and stochastic volatility models which are intuitive measure to explore volatility clustering in asset returns. The concept of volatility clustering highlights persistence of fluctuations in asset returns and challenges the assumption of constant volatility often employed in traditional financial models. Several factors contribute to the occurrence of volatility clustering in financial markets but one prominent explanation is investor behavior and market sentiment (Enow, 2022). During periods of high uncertainty or unexpected news events, market participants tend to react more strongly leading to increased volatility (Malik et al. 2005). This behavior can create a feedback loop as heightened volatility prompts further reactions and amplifies price swings (Enow, 2023). Information arrival and asymmetry in market reactions also contribute to volatility clustering where positive news tends to have a less significant impact on volatility than negative news, leading to longer-lasting volatility clustering (Pereira & Zhang, 2010). Volatility clustering has important implications for various market participants. Risk managers and portfolio managers rely on accurate volatility forecasts to assess potential losses and design effective risk management strategies. Moreover, volatility clustering affects the pricing of options and other derivatives as these instruments heavily rely on volatility estimates. Failure to account for clustering can lead to mispricing and trading inefficiencies. Market participants such as high-frequency traders, momentum traders and algorithmic trading systems also exploit stock market patterns as they employ strategies that capitalize on the persistence of volatility (Visaltanachoti & Pukthuanthong-Le, 2009). By identifying periods of high or low volatility, these market participants can adjust their positions accordingly to profit from the clustering behaviour. Therefore, the aim of this study was to investigate the historical patterns and statistical properties of volatility clustering across different financial markets and potential drivers influencing volatility clustering. In so doing, this study contributes to the existing knowledge on volatility clustering, enhance risk management practices and improve market predictions and trading strategies. The section below highlights the literature review.

2. LITERATURE

The phenomenon of volatility clustering has been a subject of interest for researchers in the field of finance for several decades and gained prominence in the 1980s and 1990s when researchers began to challenge the assumption of constant volatility made by traditional financial models (Nelson, 1990). The pioneering work of Engle (1982) who introduced the ARCH model laid the foundation for understanding and modelling volatility clustering. Since then, numerous studies have contributed to the understanding of this phenomenon and its implications for financial markets. One of the central findings from volatility clustering is the persistence of volatility where high volatility tends to be followed by high volatility and low volatility tends to be followed by low volatility (Bauwens, 2006). This clustering behaviour suggests that volatility is not randomly distributed but influenced by underlying factors that persist over time (Engle & Rangel, 2005). Volatility clustering is also often associated with long memory or long-range dependence in financial markets (Enow, 2022). This implies that the impact of past volatility shocks on current volatility can persist for an extended period. The presence of long memory has significant implications for volatility modelling and forecasting (Cont, 2007). Another notable finding in the literature of volatility clustering is the concept of asymmetry information where volatility tends to increase more sharply during market downturns or periods of financial stress compared to its decline during market upturns (Bera & Higgins, 1993). This asymmetry known as leverage effect highlights the non-linear relationship between volatility and market returns.

Understanding the underlying mechanisms behind volatility clustering is essential for comprehending its causes and dynamics. One plausible explanation is the information arrival hypothesis (Ackert et al., 2003). Market participants react to new information leading to increased trading activity and subsequent price fluctuations. As more information is revealed, volatility tends to persist until a new equilibrium is established. Investor behaviour also plays a crucial role in modelling volatility. During times of uncertainty or fear, market participants become more risk-averse amplifying price swings and contributing to clustering (Karanasos, 2014). Moreover, feedback effects and herding behaviour can further reinforce volatility clustering as investors react to and amplify each other's actions. Momentum strategies for instance take advantage of the momentum exhibited by assets during clustered volatility periods (Rahman, 2022).Volatility-based trading strategies such as volatility breakout or mean-reversion strategies aim to profit from the clustering behaviour itself. Additionally, risk managers and portfolio managers need to consider volatility clustering when assessing potential losses and designing risk management strategies. Neglecting volatility clustering can result in underestimated risk measures and ineffective hedging techniques. Therefore, the contribution of this study is of significance to the frontier of volatility modelling and adds to the debate of market anomalies and efficiencies. The section below highlights the blueprint of the study.

3. METHODOLOGY

An ARCH and its extension the GARCH was used to capture and explain volatility clustering in four financial markets namely, (JSE index), the French stock market index (CAC 40 index), Frankfurt stock exchange (DAX index), Nasdaq index, from June 14, 2018 to June 14, 2023. These models have been widely employed to capture the persistence and asymmetric nature of volatility where they incorporate lagged volatility terms, allowing for the clustering effect to be captured vividly (Engle, 1982; Endri et al., 2021; Enow, 2023). Also, these models allow for time-varying volatility by incorporating lagged squared residuals as explanatory variables. They provide a parsimonious framework to estimate and forecast volatility clustering. According to Bollerslev (1986), the ARCH and GARCH models is given by;

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

Where h_t = Conditional variance, α = error term, ϕ = ARCH term, h_{t-1} = Lag values of Conditional variance, β = GARCH coefficient and μ_{t-1}^2 = Lag square error term. All the variables where the daily returns calculated from the daily share prices from the selected stock markets. The results and analysis are presented below.

4. RESULTS AND DISCUSSION

The results and discussion presented below is was a critical section for this study as it objectively presents the analysed data as well as some key discussions that are linked to the findings. Table 1 below highlights the GARCH and ARCH outputs**.**

Table 1: ARCH and GARCH out put results

JSE				
Variable	Coefficient	Std Error	Z-statistics	P-value
Log (GARCH)	0.10%	0.10%	0.8	0.423
Intercept	1.10%	1.50%	0.77	0.4366
Lag Return	-10.40%	2.80%	-3.63	0.0003*
Variance Equation				
Intercept	0.01%	0.00%	3.29	0.001
ARCH	0.033	0.69%	4.77	0.000*
GARCH	0.935	1.47%	63.21	0.000*
CAC 40				
Variable	Coefficient	Std Error	Z-statistics	P-value
Log (GARCH)	0.14%	0.06%	2.54	0.0108*
Intercept	1.47%	0.54%	2.68	0.0073*
Lag Return	-1.26%	2.85%	-0.44	0.65
Variance Equation				
Intercept	0.01%	0.00%	7.07	0.000*
ARCH	16.70%	2.15%	7.75	0.000*
GARCH	77.70%	2.55%	30.49	0.000*
DAX				
Variable	Coefficient	Std Error	Z-statistics	P-value
Log (GARCH)	0.16%	0.06%	2.51	0.011*
Intercept	1.56%	0.59%	2.61	0.008*
Lag Return	-4.44%	3.14%	-1.41	0.157
Variance Equation				
Intercept	0.00%	0.00%	5.95	0.000*
ARCH	13.50%	1.68%	8.06	0.000*
GARCH	81.62%	2.13%	38.21	0.000*
Nasdaq				
Variable	Coefficient	Std Error	Z-statistics	P-value
Log (GARCH)	0.04%	0.05%	0.85	0.393
Intercept	0.50%	0.45%	1.115	0.264
Lag Return	-6.48%	2.98%	-2.169	0.03*
Variance Equation				
Intercept	0.01%	0.00%	4.06	0.000*
ARCH	15.58%	2.17%	7.15	0.000*

GARCH	83.10%	2.06%	40.16	0.000*
*Significant at 5%				

From table 1, the past returns of the sampled financial markets have a very weak predictive ability for future returns which was evident from the p-values of the lag returns that are greater than the 5% confidence level. Hence, observing past returns in an attempt to predict future performance may be misleading. Also, the ARCH and GARCH coefficients are all positive and less than one satisfying the stability criteria and establishes the presence of time varying properties and volatility clustering in the sampled financial markets. The results also indicate large clustering effect because the sum of ARCH and GARCH coefficients are close to one. This finding corroborates with the study of Nguyen et al. (2020) who also found significant clustering effect in financial markets. These volatility clustering may be due the market disruptions that have occurred in the past such as the dotcom crisis, 2007-2008 financial crisis and the most recent covid-19 pandemic (Topcu et al., 2021). Hence, volatility clustering is expected whenever there are market disruptions.

5. CONCLUSION

Volatility clustering is a well-documented phenomenon in financial markets and it is characterized by periods of high and low volatility. Empirical evidence confirms its existence across various asset classes and highlights its persistence over time. Volatility clustering has multiple causes including investor behavior, market sentiment, information arrival and market reactions. Its impact on risk management, derivatives pricing, trading strategies and financial stability necessitates the development of sophisticated models and risk management techniques that account for this phenomenon. As financial markets continue to evolve, understanding volatility clustering remains crucial for market participants and policymakers to navigate the complex dynamics of market fluctuations and effectively manage risks. The purpose of this study was to investigate the concept of volatility clustering in international financial markets and explore the possible drivers. The findings revealed the presence of volatility clustering in line with prior study. These clustering may be due to the recent episodes in financial markets such as the covid-19 pandemic. Hence, portfolio manager need to anticipate frequent market disruptions as a result of systemic risks in financial markets. Central banks and regulatory authorities need to implement measures to enhance market resilience, sufficient liquidity and regulate high-frequency trading activities.

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