Proceedings of the 10th International Conference on Economic Management and Green Development
DOI: 10.54254/2754-1169/2026.35907

Analysis of Financial Return Volatility Clustering from a GARCH Perspective

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Abstract. The fluctuation characteristics of financial time series have always been one of the research hotspots in the academic community. Generally speaking, financial return series have the characteristics of volatility clustering, fat tails, conditional heteroskedasticity, asymmetric shocks, etc. The above phenomena can be explained from the perspective of dynamic conditional variance by GARCH models and their extensions. This paper first introduces the basic ideas of ARCH and GARCH models, with a focus on the issue of volatility clustering of financial returns. Then, it reviews the relevant research from three aspects: model evolution, application scenarios, and practical value. It also analyzes the role of GARCH-type models in capturing volatility persistence, asymmetric impact, and risk transmission through applications in cryptocurrencies, energy assets, and high-frequency financial data. The study shows that GARCH-type models capture the volatility clustering feature of financial returns well, but there is still room to improve the modeling of extreme risk, the handling of high-dimensional assets, and model interpretability.

Keywords: Volatility clustering, GARCH model, Financial returns, Conditional heteroskedasticity, Risk transmission

1. Introduction

Financial return sequences typically exhibit distinct cluster characteristics of volatility. Financial returns display volatility clustering if large price movements tend to happen consecutively in periods of time, and small fluctuations also tend to happen consecutively in adjacent periods of time. In other words, financial return volatility has a certain degree of temporal dependence and persistence. This phenomenon is common in financial markets such as equities, foreign exchange, commodity futures, energy assets, and cryptocurrencies and is one of the characteristics of financial time series that make them different from general economic time series.

Volatility clustering in financial returns has important theoretical and practical implications. Theoretically, it means the variance of financial returns is not constant. Thus, traditional linear models that assume homoskedasticity are not appropriate for financial returns, and they are not good enough to capture market risk. Practically, volatility clustering means market risks can last for a long time. If the change in volatility is not detected and forecasted in time, investors and financial institutions may underestimate risk exposure. How to explain volatility clustering from the point of

DOI: 10.54254/2754-1169/2026.35907

view of econometrics has become an important issue in financial risk management, asset pricing, and portfolio allocation.

The insight of Engle's Autoregressive Conditional Heteroskedasticity (ARCH) model is that it can explain volatility clustering [1]. The ARCH model assumes that current volatility is affected by past shocks. Therefore, this model captures the time-varying conditional variance of financial returns. Later, Bollerslev proposed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which also takes into account the impact of past volatility on current volatility based on the ARCH model, so that volatility persistence can be explained in a more concise and effective way [2]. After that, the GARCH model has been extended, and there have arisen various forms of the GARCH model, for example, Exponential GARCH (EGARCH), GJR-GARCH, Dynamic Conditional Correlation GARCH (DCC-GARCH), and Markov-switching GARCH models, which are used to explain asymmetric volatility, dynamic correlations, volatility spillovers, and regime shifting of markets.

With the evolving market structures and trading practices in recent years, research on volatility clustering in financial returns has enlarged both in scope and in method. On one hand, for the rapidly developing cryptocurrency markets, the issues of high volatility, high-frequency trading, and cross-market risk transmission have attracted attention. On the other hand, with the growing interconnections among energy markets, clean energy assets, and many traditional financial assets, volatility clustering, which was only a concern for one asset, has become an issue of cross-market and cross-asset risk propagation. In addition, with the development of machine learning and deep learning, new tools for identifying and forecasting volatility clustering in financial returns have become available.

According to this background, this paper reviews the econometric explanations of volatility clustering in financial returns and the related literature based on GARCH-type models. The structure and contents of the paper are arranged as follows. First, the basic logic of how ARCH and GARCH models explain the clustering of volatility is presented. Second, the related research is surveyed along three aspects: model evolution, application situations, and practical value. Third, the existing defects in the literature are pointed out in terms of modeling extreme risk, high-dimensional representation, and interpretability. Finally, future research directions are proposed to provide guidance for later work.

2. The econometric explanation of volatility clustering by the GARCH model

Different from the above models that assume the variance to be constant, the ARCH model assumes that the volatility of the returns of financial assets is affected by past shocks. Therefore, if in the earlier periods markets have big shocks, the volatility may still be high in the later periods; on the other hand, if the shocks are small, market volatility may also be small in the later periods. This idea well explains the fact that in financial returns, large fluctuations tend to follow large ones and small fluctuations follow small ones, that is, the so-called volatility clustering.

Bollerslev further proposed the GARCH model on the basis of the ARCH model [2]. The GARCH model not only takes the effect of past shocks on current volatility but also takes the past level of volatility into account. It is better able to capture the persistence of financial return volatility. Compared with the ARCH model, the GARCH model can describe long-term volatility characteristics with a much simpler structure. Therefore, it is one of the most popular econometric models for describing the volatility clustering of financial returns.

The way that the GARCH model explains volatility clustering is in two points. First, it considers volatility as a time-varying conditional variance instead of a constant, that is, the model can explain

DOI: 10.54254/2754-1169/2026.35907

the change in market risk in different periods. Second, it puts the main attention on both past shocks and the past level of volatility in current volatility, that is, volatility is persistent. In this case, when there is a big event, a crisis, or a sharp change in investor sentiment, volatility can be high for a short time, and then volatility clustering appears.

On the other hand, there are some drawbacks of the standard GARCH model. For example, the standard GARCH model usually assumes that the effects of positive news and negative news on volatility are symmetric, but in fact negative news usually causes a stronger market reaction than positive news. The standard GARCH model is for the analysis of the volatility of one asset and cannot directly capture the dynamic correlation among several assets or markets. In order to solve these problems, some extended models have been studied, such as the EGARCH and GJR-GARCH models to deal with asymmetric volatility, the DCC-GARCH model to deal with dynamic correlations and volatility spillovers, and the Markov-switching GARCH model to deal with regime shifts of market conditions.

In summary, GARCH-type models give a clear econometric explanation of volatility clustering in financial returns. They help to explain why volatility has persistence and changes in phase, and they also provide the ground for the following analyses of market risk, asset co-movement, and volatility transmission.

3. Volatility clustering study based on the GARCH model

3.1. Model evolution: from univariate volatility to state transition and dynamic correlation

Usually, traditional GARCH models assume that the market volatility process keeps a quite stable structure in the whole period of the sample. In reality, financial markets could have different volatility regimes in different stages. For example, in a financial crisis, pandemic shock, or policy change, markets can be in high-volatility states, and in the period of economic stability, market volatility is relatively low. In this way, using the single-state GARCH model cannot catch the differences of volatility clustering in different market conditions.

This limitation is addressed, for example, by Markov-switching GARCH models, as these models introduce a regime-switching mechanism, and the market is then split into high- and low-volatility states, and thus the phased nature of volatility clustering is better captured. Ardia et al. did a comparative study on the performance of Markov-switching GARCH models in risk forecasting, and they found that these models can improve risk prediction to some extent for financial time series where there are clear shifts in market regimes [3]. In cases when financial markets are affected by crises, policy shocks, or changes in liquidity, introducing a regime-switching mechanism can help more to identify the evolution of volatility clustering.

From the point of view of explaining volatility clustering, the main value of the Markov-switching GARCH model is that it is not only to see whether volatility is persistent or not, but also how the persistence may vary when the market environment changes. Namely, when the market is in high-volatility states, market shocks will last longer, and volatility clustering will be stronger; when the market is in low-volatility states, the market is relatively calm, and volatility clustering is weaker. Therefore, this model is a more flexible econometric way to study the persistence of risk under different market environments.

Besides the regime-switching models, multivariate GARCH models have made the research of volatility clustering move from the study of a single asset to the study of cross-market relationships. With global financial markets becoming more and more connected, volatility clustering not only happens within the individual market but also can be passed from markets through asset prices,

DOI: 10.54254/2754-1169/2026.35907

investor sentiment, liquidity, and information channels. Multivariate GARCH models such as DCC-GARCH and BEKK-GARCH can make the analysis of the dynamic change of correlations among assets, so volatility spillovers and the risk contagion process can be revealed. It is very important for cross-market portfolio management and the prevention of systemic risk.

3.2. Application scenarios: pandemic impact, cryptocurrency, and energy markets

In recent years, the COVID-19 pandemic has been an important external shock affecting financial markets around the world. After the outbreak of the epidemic, different global markets, including equities, gold, crude oil, and cryptocurrency, had sharp volatility to some extent. The correlations and the mechanism of risk transmission of different assets change when the risk appetite of investors drops and market uncertainty goes up. Under these circumstances, the clustering of volatility in financial returns will be stronger.

Corbet et al. studied the contagion effects of the COVID-19 pandemic in gold and cryptocurrency markets and found clear evidence of market co-movement and risk contagion between gold and cryptocurrencies during the pandemic [4]. This means that, in case of extreme events, the fluctuations of asset prices do not only stay inside the single market but can also spill over to other markets by means of investor sentiment and capital flows. Therefore, volatility clustering is no longer only a feature of an individual asset return series; it may also be a cross-market co-aggregation of volatility.

Kumar et al. also studied the connectivity among the major cryptocurrencies in the normal period and in the time of the COVID-19 pandemic. They found that the pandemic amplified the dynamic linkages among the major cryptocurrencies, and market risks are easily transmitted in different crypto assets [5]. It indicates that in the crisis, both volatility clustering and risk transmission in the cryptocurrency market are intensifying at the same time, and the high-volatility states of the individual asset will spread to others quickly.

Cryptocurrency markets have 24/7 trading, high speculation, extreme volatility, and a lack of regulation, so their return series will have particularly strong volatility clustering. Information spreads faster on cryptocurrency markets, investor sentiment also changes more, and the price tends to concentrate more over a short time when compared to stock markets. In recent years, cryptocurrencies have become a focus for GARCH-type models.

Sensoy et al. used high-frequency data to look at return and volatility spillovers among cryptocurrencies, and they found the existence of high-frequency volatility transmission effects that are significant and change with the changing of the market [6]. Thus, it can be seen that volatility clustering in cryptocurrency markets is not only shown for the movements of the price of every coin but also in the co-movement of inter-coin and the transmission of risk. From the investors' point of view, if such high-frequency volatility clustering and spillover effects are not taken into consideration, the real risk of the investment portfolio could be underestimated.

From the perspective of post-pandemic return and volatility spillovers in cryptocurrency markets, Phiri and Anyikwa studied return and volatility spillovers in cryptocurrency markets. Their study found differences in risk transmission among different crypto assets across different time scales, and some major cryptocurrencies may become the main sources of risk transmission under certain market conditions [7]. This means that volatility clustering in the cryptocurrency market has multi-scale characteristics, that is, volatility persistence in the short term, medium term, and long term may be very different.

Stejskalova and Krampla applied the DCC-GJR-GARCH model to high-frequency cryptocurrency data to study volatility spillovers. Their analysis uses dynamic conditional

DOI: 10.54254/2754-1169/2026.35907

correlation models with asymmetric volatility specifications to identify dynamic correlations and asymmetric responses to shocks among different cryptocurrencies [8]. This approach is in line with the new trends of research on volatility in cryptocurrency markets: the use of high-frequency data, multi-asset analysis, and asymmetric modeling.

In general, the fluctuations of energy market prices are caused by supply-demand factors, geopolitical reasons, macroeconomic policies, and energy transition, and therefore have some volatility clustering features. Particularly in the crude oil market, natural gas market, and clean energy asset market, after some external shocks, price volatility keeps on within a period of time. With the development of the green transition all over the world, the co-movement of the volatility of fossil fuel, clean energy, and traditional financial assets has got more and more attention.

Ozkan et al. also used the DCC-GARCH method to investigate the dynamic volatility relationships between fossil fuels, clean energy, and other major asset classes. They found that there are complicated dynamic correlations among different energy and financial assets, and market shocks may be transmitted to other asset markets through energy price channels [9]. From this study, it can be seen that volatility clustering may not only exist in the energy market but also spill over to stock, bond, and other financial markets in the circumstance that energy price uncertainty is on the rise and the green transition is becoming more rapid.

3.3. Application value: risk persistence, risk measurement, and hybrid forecasting

The most direct application value of GARCH-type models is to find the persistence of financial market risks. Because volatility clustering means that risk will exist in some periods, the assumption of constant variance may underestimate market risk. The GARCH model estimates conditional volatility dynamically according to past return data, so as to reflect the changes of market risk in different time periods. When markets have large shocks, the model can catch the process of volatility rising and how long it is lasting; and when markets slowly stabilize, it can also reflect the decline of volatility.

Volatility is an important building block in financial risk management for the calculation of value at risk, expected loss, and metrics for stress testing. If financial returns have volatility clustering, but the risk model does not capture this feature, then the risk measurements may be biased. If conditional heteroskedasticity is modeled by GARCH-type models, then the future level of risk can be better estimated. Therefore, GARCH-type models are used very often in market risk management by banks, funds, and financial institutions.

In real financial markets, negative news will cause more volatility than positive news. For example, falling stock prices, financial crises, or other unexpected events usually push the market into more panic and volatility will increase a lot. Models like GJR-GARCH and EGARCH can investigate the asymmetric effect of positive and negative shocks on volatility, and thus can better explain the phenomenon of asymmetric volatility clustering in financial returns.

With the increasing volume of financial data and the development of computing technology, the traditional GARCH model is also combined with machine learning and deep learning methods to improve volatility forecasting. The traditional GARCH model has strong economic interpretability and can clearly explain the mechanism of volatility clustering well, but it has some limitations in dealing with high-dimensional data, nonlinear structures, and complicated market patterns. The machine learning approach is very good at data fitting and prediction, but most machine learning approaches lack strong economic interpretability.

Ampountolas studied the performance of GARCH models and support vector regression models in the forecast of commodity and financial markets. It was shown that in some cases machine

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learning methods can give better forecasting accuracy in the market, but GARCH models are important benchmarks [10]. It means that in the research of volatility clustering, GARCH models are not replaced by machine learning techniques but have basic value in the explanation of the persistence of financial market volatility.

The DeepVol model was proposed by Moreno-Pino and Zohren, using dilated causal convolutions to predict future realized volatility from high-frequency data. In the study, they show that deep learning methods can better capture the nonlinear structure and long-term dependences in high-frequency financial data [11]. In comparison with the traditional GARCH model, deep learning models give advantages in predicting complicated volatility patterns, but the interpretability and robustness of these deep learning models still need to be checked.

In other words, future research on volatility clustering is not about a choice between GARCH and machine learning methods, but about how to combine both. For example, one could use GARCH models to get features for conditional volatility and feed them into machine learning models as input variables. Or one could construct hybrid models in order to keep the economic interpretation of GARCH but also get higher predictive accuracy.

4. Limitations of current research and future research directions

4.1. Insufficiency of existing research

On the one hand, first, some studies still use only univariate GARCH models. Such models are not able to capture well the interdependencies among several assets and also across markets. When the integration of financial markets becomes deeper, the clustering of volatility is often due to cross-market and cross-asset risk transmission, so it is not very adequate to study volatility in only one asset.

Second, traditional GARCH models have limited capacity to model extreme risks and sudden events. Because extreme shocks in financial markets are usually sudden, nonlinear, asymmetric, and the tail risks of standard GARCH models may not be well captured. In the future, tools such as heavy-tailed distributions, extreme value theory, or quantile methods should be further taken into the model to make the model better explain extreme volatility clustering.

Third, although machine learning and deep learning methods do have advantages in predictive accuracy, they have poor interpretability. The research of volatility clustering is not only concerned with whether the prediction is right, but also why volatility is persistent, how risks propagate, and how different markets interact. Without economic interpretability, these models may have some limitations in applications related to financial regulation and investment decision making.

Finally, differences in data frequency, sample periods, asset types, and model specifications of different studies result in insufficient comparability of the results of the studies. In the cases of cryptocurrency and clean energy markets where developments in the market happen very quickly, sample selection can still have a big impact on empirical results. Therefore, in future research, the focus should be put more on robustness checks, out-of-sample forecasting, and multi-model comparison.

4.2. Future research directions

First, multivariate and high-dimensional GARCH models may be further developed. With the increasing interconnectivity of financial markets, volatility clustering is not only for individual asset return series but also for the transmission of risk in different markets. Thus, how to deal with high-

DOI: 10.54254/2754-1169/2026.35907

dimensional asset correlation structures and still keep the model estimable is one of the directions for future work.

Second, the integration between GARCH models and machine learning methods can be strengthened. On one hand, traditional GARCH models can well describe the economic meaning of volatility clustering; on the other hand, machine learning techniques are especially good at dealing with nonlinear relationships. It is interesting for future research to construct hybrid forecasting frameworks with volatility features that are extracted by GARCH models and machine learning algorithms to improve both forecasting ability and interpretability.

Third, greater attention should be paid to the mechanisms of volatility clustering during extreme events. The risk relationship among assets may change in the period of the COVID-19 pandemic, the energy crisis, geopolitical conflict, and liquidity shock in the financial market. For future study, methods such as Markov-switching GARCH, DCC-GARCH, and extreme value theory can be used to identify volatility persistence and the way of risk contagion more exactly under extreme market conditions.

Fourth, the research on emerging financial assets can be continued. With the development of cryptocurrency, carbon market, clean energy stock, and ESG assets, the appearances of volatility clustering have become more complicated. Future research may compare the differences of the volatility clustering character of traditional and emerging assets, and enrich the application scope of GARCH-type models.

5. Conclusion

This paper reviews the econometric interpretation of GARCH-type models and related literature. The issue of volatility clustering in financial returns is discussed. The phenomenon of volatility clustering in financial returns means that market risk is not randomly or uniformly distributed, but has significant temporal persistence. ARCH and GARCH models explain this phenomenon from the perspective of conditional heteroskedasticity. They are essential econometric tools for financial volatility research. As the studies get advanced, GARCH-type models go beyond the standard forms. GJR-GARCH, EGARCH, DCC-GARCH, and Markov-switching GARCH are some of the extensions of the GARCH model. These extended models can further improve the ability to capture asymmetric volatility, dynamic correlations, volatility spillovers, and regime shifts in markets. In recent years, the developments of cryptocurrencies, energy assets, clean energy assets, and high-frequency financial data give new samples and methodologies for studying volatility clustering.

In summary, GARCH-type models are still important tools to explain volatility clustering in financial returns. They not only show the persistence of volatility but are also frequently used in risk measurement, volatility forecasting, and cross-market risk transmission analysis. The existing literature still has some problems: first, the univariate model cannot well catch the complicated interdependency among multiple markets and high-dimensional assets; second, traditional GARCH models do not have enough power to explain extreme events and tail risk; third, even if machine learning models have better ability in forecasting, their economic interpretability is still weak. Future research can combine high-frequency data, machine learning techniques, and extreme risk analysis to improve both prediction performance and model interpretability to better support financial risk management and asset allocation practices.

DOI: 10.54254/2754-1169/2026.35907

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