An Event-Driven Analysis of Volatility Forecasting for U.S. and Chinese Technology Indices: Application of GARCH Family Models

Lan Huang
City University of Hong Kong, Economics and Finance Department, Hong Kong, China

Abstract: This study investigates the distinct volatility dynamics of the U.S. (NASDAQ-100) and Chinese (ChiNext) technology stock markets in response to major geopolitical and economic shocks. Utilizing daily data from 2017 to 2024, the study employs GARCH, EGARCH, and TGARCH models to analyze market behavior, with a specific focus on four key events including the U.S.-China Trade War and the COVID-19 pandemic. The results reveal a strong, classic leverage effect in the NASDAQ-100, for which the EGARCH model provides the best fit. In contrast, the ChiNext index exhibits a weaker, threshold-based asymmetry best captured by the TGARCH model. While the models effectively captured event-driven volatility through their asymmetric components, diagnostic tests indicate that standard GARCH frameworks, though adequate for the NASDAQ-100, are insufficient to fully model the more complex risk structure of the ChiNext market. The findings underscore that risk characteristics are fundamentally market-specific, necessitating tailored modeling approaches for effective global risk management.

Keywords: Volatility Forecasting; GARCH; Event Study; Technology Indices; Leverage Effect

1. Introduction

1.1 Background

The modern global economic environment has been marked by a high level of uncertainty, which has been caused by a number of factors such as the outbreak of the global health crisis, geopolitical realignment, and technological change. In this context, the world technology market has become a key driver of economic development and a center of instability in the market. The interdependence of the contemporary financial markets implies that the shocks that have happened in one sphere may rapidly spread all over the world, which is acutely noticed in the conditions of the COVID-19 pandemic [1]. The market responses of this time indicated the susceptibility of even the strongest economies to abrupt, systemic shock and that the proper modeling and prediction of financial volatility has never been more important to investors, policymakers, and risk managers [2].

1.2 The U.S.-China Geopolitical Context

The economic and technological competition in the world is dominated by the United States and China. In addition to dominating their technology market, they boast of sophisticated supply chain networks and interdependent financing webs. This relationship has been compromised by many significant economic and geopolitical trends that have resulted in a great deal of uncertainty on the market. The most important ones are the U.S.-China Trade War that began in 2018, the announcement of the COVID-19 pandemic that occurred in 2020, the introduction of the U.S. CHIPS and Science Act in 2022, and the extension of the U.S. export ban on AI chips in 2023. The trade war, as one such, is a product of the enormous impact of financial contamination flowing through the markets of the planet demonstrating how enormous such events are [3]. They can be regarded as natural experiments that will be useful to learn about the risk profile and resilience of the Chinese and American technology industries [4].

1.3 Research Problem

Since there is a high degree of financial interdependence between the Chinese and American markets, volatility dynamics in such markets are an international issue to consider [5]. The greatest issue, however, is that they are too different in structure. The U.S. market, which is the NASDAQ-100, is highly developed, and it is a mature market with institutional investors leading. Conversely, the Chinese market, which is depicted by the ChiNext index, is an emerging market that is growing at a high rate and has a different regulatory system and a higher ratio of retail investors. These structural differences imply that the two markets can process information and respond to external shocks in significantly different ways. Making homogeneous risk structure assumptions or using a single volatility model may hence result in wrong predictions and ineffective risk evaluations.

1.4 Objectives

This paper will attempt to compare and contrast the volatility nature of the index NASDAQ-100 and ChiNext between 2017 and 2024. The main goal is to identify the most appropriate GARCH-family model for each market by explicitly testing for leverage effects (using the EGARCH model) and threshold asymmetry (using the TGARCH model) to determine whether asymmetric volatility exists and in what form. This study seeks to learn how the shocks are discounted in the volatility of every market through introducing the above-mentioned geopolitical and economic incidences as a literal consideration. The paper has three contributions; firstly, it gives a head to head analysis of the risk structure of the two important technology indexes in the globe, secondly it evaluates the sufficiency of the standard GARCH models in explaining their behavior during turbulent times, and thirdly, the paper gives valuable information to cross-border investors on managing risk across markets.

2. Literature Review

2.1 Theoretical Foundation of Volatility Modeling

Financial time series volatility modeling has been a main topic for decades in econometrics. The basic difficulty is to model the phenomenon of volatility clustering, whereby large price changes are succeeded by other large changes, and calm periods are succeeded by calm periods. This task was, in turn, given the seminal framework of the Autoregressive Conditional Heteroskedasticity (ARCH) model and its generalization by Bollerslev, the GARCH model [6]. GARCH models have become the standard in the industry and academia because they have been shown to be effective in modeling the time-varying and persistent nature of financial volatility [7]. This structure has been developed over time to produce a set of models that are intended to model more subtle market dynamics, including the asymmetry of positive and negative news on volatility.

2.2 Event Studies and Market Shocks

Much of the literature has been devoted to the study of the response of financial markets to large-scale, unexpected events. COVID-19 pandemic is a global systemic shock that has been given special consideration in recent studies. It has been found that the effect of the spread of the virus was rapid and adverse to all stock markets around the globe with precedent volatility levels [8]. On the same note, the China-U.S trade war has been cited to have been a key factor in market instability leading to financial contagion and risk spillovers between the two nations [3]. The transmission of volatility, the so-called spillovers between the Chinese and the U.S. markets, has also been studied, with the direction and strength of the spillovers being observed to be enhanced when the markets are going through a period of crisis [9]. These findings establish the fact that significant external events are one of the main determinants of the dynamics of volatility that this paper attempts to model.

2.3 Asymmetric Volatility and Comparative Studies

The main weakness of the standard GARCH model is that it assumes that both positive and negative shocks with equal strength have the same impact on volatility. In fact, negative news tends to be much more significant, a process that is called the leverage effect. This has seen the creation of asymmetric models such as the Exponential GARCH (EGARCH) and the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH or TGARCH). These statistical models are theoretically supported by the concept of information asymmetry, when various market participants have dissimilar information levels [10]. A number of studies have performed comparative studies on U.S. and Chinese market volatility and have frequently discovered structural differences in their behavior [4]. Nevertheless, the direct comparison of their technology sectors in terms of a combination of asymmetric GARCH models in the framework of the recent, specific events in the geopolitical sphere is a pressing sphere to be studied further.

2.4 Research Gap

Although the current literature has determined the usefulness of GARCH models, the role of significant events and the existence of spillovers between the U.S. and China, the granular and comparative analysis of their technology sectors is underdeveloped. The purpose of this paper, therefore, is to address this gap by undertaking a head-to-head analysis of the NASDAQ-100 and ChiNext indices. With the use of a variety of GARCH-family models, the volatility persistence in each market can be quantified and the nature of the asymmetric responses of each market to shocks will be identified. This strategy will enable a better appreciation of whether the risks of these two crucial markets are converging or if their structural variations are still contributing to divergent behavior [5].

3. Data and Methodology

3.1 Data

The research data were the closing prices of the U.S. NASDAQ-100 and the Chinese ChiNext technology index daily. The data used in this study consist of daily closing prices for the U.S. NASDAQ-100 and the Chinese ChiNext technology indices, sourced from Yahoo Finance and the Wind Financial Terminal, respectively. The time frame of January 2017 to December 2024 was chosen because it will be available throughout the entire duration of the chosen geopolitical and economic events. The data were filtered and processed to obtain a final sample of 2,011 observations on a day (NASDAQ-100) and 1,942 (ChiNext index). The primary variable in the analysis is the percentage log return per day, as calculated as follows. Such a transformation is typical in financial analysis as it tends to put the time series in a stationary state and produces a continuously compounded rate of return [11]:

$$r_t = 100 \times \log\left(\frac{P_t}{P_t\text{-}1}\right) \quad (1)$$

Where P_t is the price on the closing day t?

3.2 Event-Driven Dummy Variable

To quantitatively assess the impact of the four major events on market volatility, an event-study framework was adopted. A dummy variable, event, was constructed to take the value of 1 during a specified window around each event and zero otherwise. This approach captures the heightened market anticipation and reaction immediately before and after a significant announcement. A 21-day window, corresponding to Trading days around the event date were chosen to balance capturing the event's impact without overly diluting it. The implementation of this variable was achieved in the R programming language using the following logic.

```
#Create event window function(±10 trading days around event)
create_event_dummy-function(dates,event_dates,window =10){
  dummy<-rep(o,length(dates))
  for(event in event_dates){
    event_idx<-which(dates =event)
    if(length(event_idx)>0){
      start_idx<-max(1,event_idx -window)
      end_idx<-min(length(dates),event_idx
+window)
      dumy[start_idx:end_idx]<-1
    }
  }
return(dummy)
}
```

Code Snippet 1: The create_event_dummy R function

This function systematically identifies the event dates within the time series and assigns a value of 1 to all observations falling within the specified window, creating the event variable used in the subsequent volatility models.

3.3 Volatility Modeling Framework

This study employs a comparative approach, utilizing three distinct models from the GARCH family to analyze the volatility structure of each index. All models were specified to include the event dummy variable as an external regressor in the variance equation to directly test its impact.

The baseline model is the standard GARCH(1,1), which captures symmetric volatility clustering[6]. Its conditional variance, ht, is defined as:

$$h_t=\omega+\alpha\varepsilon_{t\text{-}1}^2+\beta h_{t\text{-}1} \quad (2)$$

Where ω is the constant, α measures the reaction to past shocks ($\varepsilon_{t\text{-}1}^2$), and β measures the persistence of volatility from the previous period ($h_{t\text{-}1}$).

To test for asymmetric effects, two additional models were employed. The Exponential GARCH (EGARCH(1,1)) model captures the leverage effect by modeling the logarithm of the conditional variance. Its variance equation is given by:

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha \frac{|\varepsilon_{t-1}|}{(ht)^{1/2}} + \gamma \frac{\varepsilon_{t-1}}{(ht)^{1/2}} \quad (3)$$

Here, the γ term is central; a negative and significant γ indicates the presence of a leverage effect, where negative shocks have a greater impact on volatility than positive shocks.

The Threshold GARCH (TGARCH(1,1)) model, also known as the GJR-GARCH model, captures asymmetry using a different mechanism:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + \beta h_{t-1} \quad (4)$$

In this model, is a dummy variable that equals one if the past shock occurred. is negative and zero otherwise. A positive and significant γ indicates that negative shocks have an additional, amplifying effect on volatility.

The estimation of these models was conducted in R using the rugarch package. To account for the observed fat-tailed nature of financial returns, a Student's t-distribution was assumed for the error terms. The following code snippet illustrates the typical model specification.

```
spec_egarch<-ugarchspec(
  variance.model=list(
    model ="eGARCH",
    garchorder =c(1,1),
    external.regressors =event_matrix
),
mean.model =list(
    armaorder =c(0,0),
    include.mean =TRUE
),
    distribution.model ="std"
)
```

Code Snippet 2: The ugarchspec R function for the EGARCH model

3.4 Evaluation Criteria

The suitability of the three models for each market was assessed based on both in-sample fit and out-of-sample forecast accuracy. For in-sample evaluation, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used, with lower values indicating a better model fit. For out-of-sample evaluation, the models were used to forecast the last 20 days of volatility, and the accuracy was measured by the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), where lower values signify superior predictive power. Finally, the adequacy of each model was validated through diagnostic tests, including the Ljung-Box test for autocorrelation in the standardized residuals and the ARCH-LM test to ensure no remaining ARCH effects were present.

4. Empirical Results

4.1 Descriptive Statistics and Preliminary Tests

The initial analysis of the return series for both indices reveals characteristics typical of financial assets. The ChiNext index demonstrated higher inherent volatility, with a standard deviation of 1.7388, compared to 1.4613 for the NASDAQ-100. Both series exhibited significant leptokurtosis, with kurtosis values of 10.08 for the NASDAQ and 10.99 for the ChiNext, far exceeding the value of 3 for a normal distribution. This "fat-tail" property indicates that extreme return events are far more common than would otherwise be expected.

Formal statistical tests confirmed these observations. The Jarque-Bera test for normality was rejected with extreme significance for both indices ($p < 0.001$), validating the choice of a Student's t-distribution for the GARCH models. Furthermore, the ARCH-LM test was also highly significant for both markets ($p < 0.001$), confirming the presence of strong volatility clustering and formally justifying the use of the GARCH framework for the analysis. The visual representation of the daily returns in Figures 1 and 2 clearly illustrates the volatility clustering phenomenon, with distinct periods of high and low turbulence.

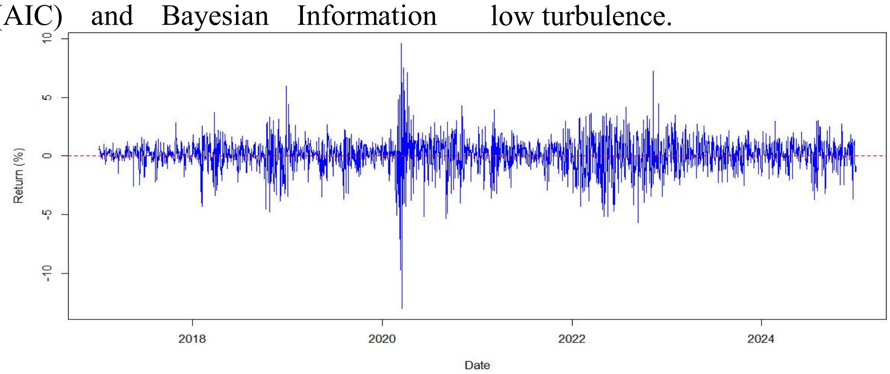

Figure 1. NASDAQ-100 Daily Returns

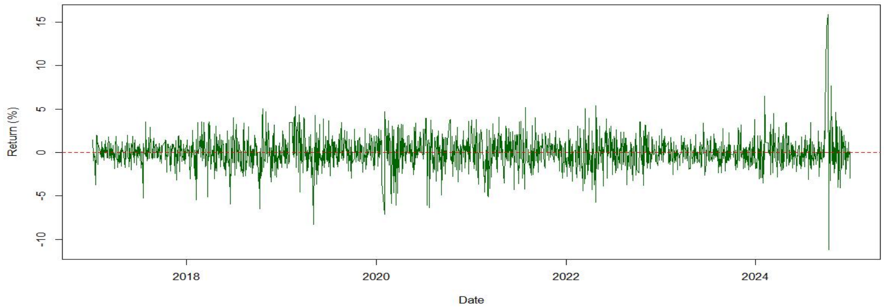

Figure 2. ChiNext Daily Returns

4.2 NASDAQ-100 Volatility Model Results

The estimation results for the NASDAQ-100 index provided a clear and decisive outcome. Based on the in-sample fit criteria, the EGARCH(1,1) model was found to be unequivocally superior, registering the lowest AIC (3.1543) and BIC (3.1738) values. The detailed coefficients of the EGARCH model reveal several key insights into the market's dynamics. The volatility persistence as 0.972860 and highly significant, indicating that shocks to volatility in the U.S. technology market are extremely persistent.

The most critical finding from this model is the asymmetry term (γ_1), which had a coefficient of 0.197306 and was highly statistically significant ($p < 0.001$). This provides strong evidence of a classic leverage effect, confirming that negative news has a significantly larger impact on volatility than positive news of the same magnitude [12]. However, the coefficient for the event dummy variable (vxreg1) was found to be statistically insignificant ($p = 0.169$). The visual evidence presented in Figure 3, which compares the conditional volatility estimated by all three models, powerfully corroborates these findings. The plot clearly shows the EGARCH model estimating a much higher level of volatility during periods of market stress, particularly the 2020 crash, providing a compelling visual illustration of the leverage effect at play.

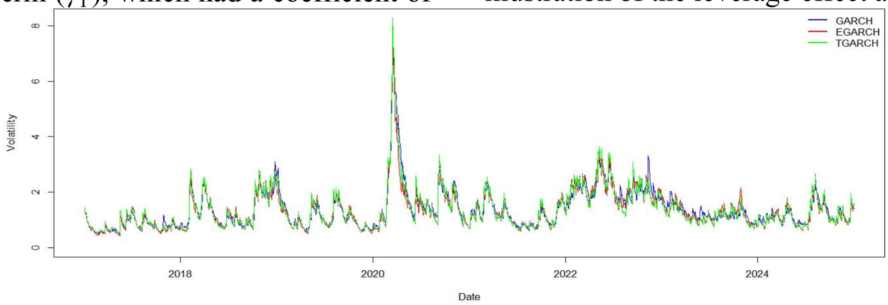

Figure 3. NASDAQ-100 Volatility Comparison

4.3 ChiNext Volatility Model Results

The results for the ChiNext index presented a more complex picture. Based on the Akaike Information Criterion, the TGARCH (1,1) model provided the best relative fit among the three candidates, with the lowest Akaike Information Criterion value of 3.7267. However, the ultimate adequacy of this model is questionable as will be discussed in the diagnostic section. The coefficients for this model showed that volatility was also highly persistent, with a Term of 0.889840. The asymmetry term (γ_1) was 0.041507 with a p-value of 0.066, making it only marginally significant. This suggests that while some evidence of asymmetric volatility exists in the Chinese technology market, it is substantially weaker and less pronounced than the leverage effect observed in the NASDAQ. Similar to the U.S. market, the event dummy variable (vxreg1) was found to be highly insignificant.

Figure 4 provides a visual comparison of the volatility estimates for the ChiNext index. Unlike the NASDAQ plot, the EGARCH model does not consistently produce the highest volatility estimates. Instead, the TGARCH and standard GARCH models appear more reactive to market shocks, visually supporting the statistical finding that a different volatility structure is at work in the ChiNext market.

5. Discussion

5.1 The Asymmetry Dichotomy: A Tale of Two Markets

The empirical results reveal a fundamental dichotomy in the risk structures of the U.S. and Chinese technology markets. The strong and highly significant leverage effect found in the NASDAQ-100 is a hallmark of a mature, information-efficient market. This phenomenon is often linked to the concept of information asymmetry, where negative news is processed more urgently by sophisticated institutional investors, leading to a disproportionate increase in volatility. The clear superiority of the EGARCH model confirms that this dynamic is a core feature of the U.S. tech sector.

In stark contrast, the ChiNext market does not exhibit such a clear-cut leverage effect. The TGARCH model's marginal superiority suggests a weaker, threshold-based asymmetry. This difference is likely attributable to the distinct structural characteristics of the Chinese market, including a different regulatory environment and a greater influence of retail investor sentiment. This finding carries significant implications, demonstrating that the mechanisms through which news and shocks are translated into market risk are not universal but are instead deeply contingent on the specific market's structure [13].

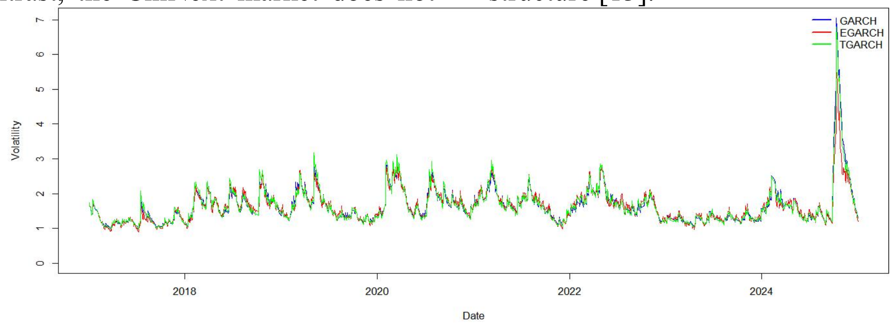

Figure 4. ChiNext Volatility Comparison

5.2 Re-interpreting Event Impact

A particularly nuanced finding of this study is the statistical insignificance of the event dummy variable in the best-fitting models for both markets. This result should not be misinterpreted as evidence that the events were inconsequential. On the contrary, the volatility plots clearly show massive spikes corresponding to these events. The interpretation is subtler: the GARCH models, particularly the asymmetric ones, were powerful enough to capture the heightened volatility without needing an additional, explicit shock term.

These geopolitical and economic events generated a significant amount of negative "news sentiment" and created substantial "economic policy uncertainty"[2]. The models' asymmetric components (γ_1) effectively absorbed the impact of this negative information, correctly identifying it as a powerful trigger for the markets' inherent risk structures. In essence, the events did not introduce a new type of risk but rather acted as a catalyst for the latent leverage and asymmetry effects already present, a finding that highlights the robustness of the asymmetric GARCH framework [12].

5.3 Model Adequacy and Market Complexity

The final layer of analysis involves assessing the adequacy of the models themselves through diagnostic testing, which revealed another critical difference between the two markets. For the NASDAQ-100, the diagnostic tests on the residuals of the EGARCH model yielded high p-values, confirming that the model was well-specified and had successfully captured the underlying volatility dynamics. Figure 5 provides visual evidence of this, showing no remaining significant patterns in the squared residuals.

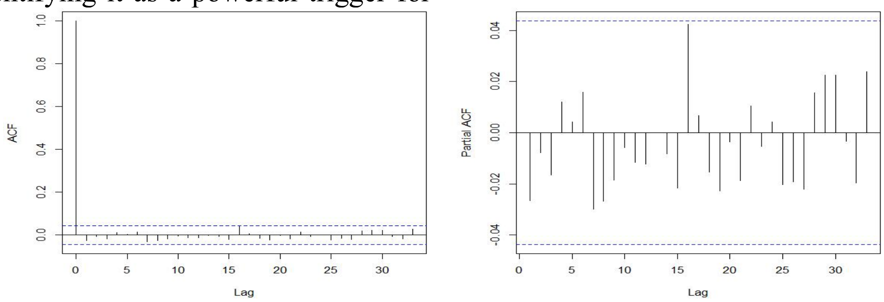

Figure 5. NASDAQ EGARCH - ACF of Squared Residuals

More importantly, the diagnostic tests for the best-fitting ChiNext model (TGARCH) failed decisively, with the Ljung-Box and ARCH-LM tests returning highly significant p-values and in stark contrast to the NASDAQ results. This is a major finding of the paper [14], which indicates that while the TGARCH model was the best among the candidates, it was ultimately insufficient to fully capture the complex volatility structure of the ChiNext market. Figure 6 visually supports this conclusion, showing that significant autocorrelation patterns remain in the squared residuals even after modeling. This suggests that the risk dynamics of the Chinese technology market are more complex and may be driven by factors such as regime shifts or jumps that are not accounted for by standard GARCH frameworks [15].

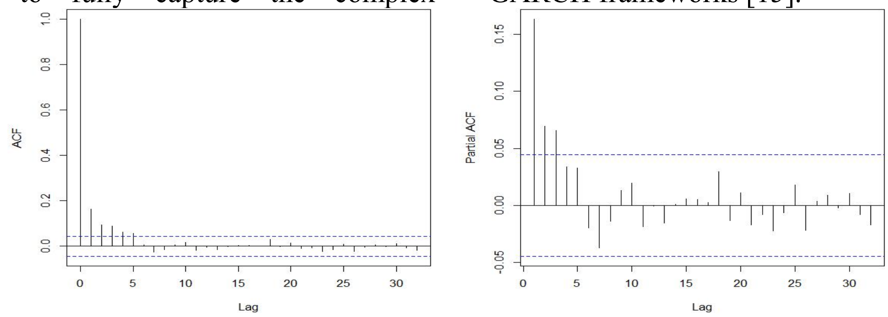

Figure 6. ChiNext TGARCH - ACF of Squared Residuals

6. Conclusion

6.1 Summary of Findings

The Chinese ChiNext technology and U.S. NASDAQ-100 index were observed and compared to one another within the framework of the main shifts in the geopolitics and economy. There were 3 significant outcomes of the study. To begin with, although the NASDAQ is slightly higher in volume, the volatility is also very intense in both markets [8]. Second, the risk structure between the American and the Chinese market is radically different as the American market can be characterized by a solid and traditional leverage effect which can be effectively analyzed based on the EGARCH model, whereas the Chinese market has a weaker and threshold asymmetry whose best relative fit is offered by the TGARCH model. Thirdly and most importantly, it was discovered that, although the GARCH-family models were effective in the case of the NASDAQ-100, none of the models were effective in the multifaceted volatility characteristic of the ChiNext index, as indicated by their inability to pass diagnostic tests.

6.2 Implications

The practical implications of the research findings on international investors and risk managers are enormous. Clearly, as evidenced by the apparent structural disparities between the two markets, a universal answer to risk modeling is essentially flawed [1]. The portfolio, the hedging strategy, and the risk assessment must be market-specific to the asymmetric dynamics of each market [13]. A very crucial indication that the usual risk measures may be underpricing the realities of the volatility within this vast emerging market is the poor performance of the model of the ChiNext market [11].

6.3 Limitations and Future Research

A major limitation of the study was that the volatility trend in the ChiNext market could not be satisfactorily explained using the models used. The Chinese ChiNext technology and U.S. NASDAQ-100 indices were followed and compared to each other in the framework of the major geopolitical and economic events. The study came up with three main outcomes. Firstly, however, in both markets despite a slightly higher volume of the NASDAQ, volatility remains very high [7]. Such a limitation, however, is a straightforward and strong line to follow to conduct additional research. More advanced econometric and machine learning methods could be employed to get a better insight into this complex industry. More complex and non-linear models or hybrid research methods such as integration of GARCH models with neural networks may be adopted to determine the time-varying determinants of the risk.

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