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Comparative Volatility Analysis of USA and China Stock Market Indices using GARCH Family Models

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Abstract:
The goal of this article is to look into the movements of two economic powers, the United States America and China, as well as the volatility spillover between the United States of America and China. Furthermore, the objective of this research is to compare and contrast the accuracy of forecasts made using univariate volatility models with those made using the Normal, Student-t, and Generalized Error models. Student t's Distribution with df and GED with Fixed Parameter Distribution, constructs in predicting stock volatility between the United States of America and China, based on 560 daily observations from the United States stock market (S&P 500 Index) and China's stock market (Shanghai Stock Exchange) (SSE Composite index and HANG SENG index).Advanced econometric models are used to achieve the research-based objectives i.e. The EGARCH (exponential generalized autoregressive conditional heteroscedastic) models (Chang, McAleer, & Tansuchat, 2012) have been applied to the data from January 27, 2000, to March 24, 2023. Asymmetry in volatility transmitting patterns, the movement of shocks with higher positive and negative magnitudes, and the model's suitability are all examined in the study. The potential benefits and dangers of

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investing are another focus of this empirical investigation. The fitness of financial series returns in the EGARCH model is one outcome. Other outcomes include the movement of financial series, volatility sketching, a description of the data and properties of the EGARCH model, and the fitness of series returns. The results show that, in the long run, the market in question is integrated. The results also demonstrate that the Chinese market mirrors the behaviour of the USA market and that investors have limited avenues for diversification at present. The results of the EGARCH model indicate that there were asymmetric volatility spillover effects between the USA and Chinese markets during the studied time periods. Based on a reliable technique that enables the examination of the dependence structure between the sample variables, this study also investigates co-movement in China. For investors looking for global investment diversification options, the findings offer helpful information.

Keywords: volatility, forecasting, EGARCH models, stock market, co-movement, economic interdependence

JEL classification: C5, C32, C58. E44, G15.

1. Introduction

The volatility of the stock markets in the United States of America and China has significant implications for global financial stability. These two economies are the world's largest, and their stock markets have a significant impact on global capital flows and investor sentiment. Studying the volatility of these markets is crucial for investors, policymakers, and researchers to understand the underlying economic forces driving these fluctuations. Volatility refers to the degree of variation of prices or returns over time (Okorie & Lin, 2020) & (Raja Ram, 2020). The stock markets of the USA and China have experienced significant volatility in recent years due to various factors, including geopolitical tensions, trade disputes, and the SARS-CoV-19 pandemic. Due to the high degree of economic interdependence between these two countries, the stock markets of both are highly intertwined and responsive to developments in the other. In order to make sound decisions, investors in these markets need to grasp the dynamics underlying volatility. Policymakers should monitor volatility to identify potential risks to financial stability and take appropriate measures to mitigate them. Researchers studying the volatility of these markets can contribute to the development of effective risk management strategies. Hence, it is important to examine the volatility of the US and Chinese stock markets with the different volatility models.

One way to model the volatility of time series data is by using different kinds of volatility models (Gunay, 2020) & (Kilian, 2008).These models are designed to capture the patterns of volatility in the data and provide insights into how the volatility changes over time. The ARCH model, the Generalised ARCH model, the Exponential Generalised ARCH model, and the time-varying GARCH model are all well-known volatility models in financial analysis. The ARCH model assumes that the volatility of the data is related to the past squared errors, while the GARCH model extends the ARCH model by incorporating lagged volatility terms (Harvey & Sucarrat, 2014) The EGARCH model allows for asymmetric volatility, while the TGARCH model incorporates the leverage effect (Peter, Huang, & Shek, 2012). By using these different models, financial analysts can better understand the patterns of volatility in stock markets and make more informed investment decisions.

Asymmetric volatility models are increasingly becoming more important in financial modeling and risk management compared to symmetric volatility models. The primary reason for this is that financial markets often exhibit asymmetry in the behavior of volatility. For instance, stock prices may rise gradually, but when there is a sudden drop, the volatility can increase significantly. Asymmetric volatility models capture such behavior by allowing for different responses to positive and negative shocks to the market (Hailemariam & Smyth, 2019) & (Hawaldar, Rajesha, & Sarea, Causal Nexus between the Anamolies in the Crude Oil Price and Stock Market, 2020). In contrast, symmetric models assume that both positive and negative shocks impact volatility equally (Pavlyshenko, 2020). Asymmetric models are more realistic in capturing complexity of market dynamics in the financial sector because they allow due to fact that investors react differently to gains and losses. For instance, in a market downturn, investors may become more risk-averse, leading to higher volatility, while in an upswing, they may become more optimistic, leading to lower volatility. Moreover, asymmetric models can provide more accurate forecasts of future volatility, which is crucial for risk management and pricing of financial instruments. Asymmetric models offer a more nuanced understanding of the behavior of financial markets and provide better tools for managing financial risk (Peter, Huang, & Shek, 2012). They are increasingly being used in areas such as asset pricing, portfolio optimization, and derivative pricing, where accurate estimation of volatility is critical (Pindyck, 2004). As the financial industry becomes more sophisticated, the importance of asymmetric volatility models is only set to increase further.

Among the various types of asymmetric volatility models, the Exponential Generalized Autoregressive Conditional Heteroskedasticity model (EGARCH) is considered best in terms of effectiveness. The EGARCH model is a popular time series model used in financial modeling and econometrics to capture the asymmetric volatility patterns that are commonly observed in financial markets. Unlike other models, the EGARCH model is more realistic in its capture of the intricate dynamics of financial markets because it allows both positive and negative shocks to have different effects on volatility. The EGARCH model is particularly useful for modeling financial returns as it accounts for the influence of previous shocks on the current level of volatility. The EGARCH model is also capable of capturing the persistence of volatility, which is a crucial characteristic of financial markets (Choudhary, 2020). Moreover, the EGARCH model allows for the incorporation of other variables that can affect volatility, such as macroeconomic variables or news events. The EGARCH model has become a standard tool in financial modeling and risk management due to its flexibility and accuracy in capturing the complex dynamics of financial markets. Its ability to model asymmetric volatility patterns and incorporate other variables makes it a reliable choice for financial analysts and traders. As financial markets continue to evolve, the importance of the EGARCH model is set to increase further, cementing its position as the most efficient asymmetric volatility model. The purpose of this research is to examine and make projections about volatility of significant indices of the USA and China.

2. Literature Review

Extensive and diverse research has been conducted on GARCH family models and their empirical applications. (Dedi, Yavas, & McMillan, 2016). Consider the fact that the literature on multivariate volatility modelling remains an active area of study. Many researchers (Almeida & Hotta, 2014), & (Glosten, Jagannathan, & Runkle, 1993) used financial econometrics i.e., using the skewness and asymmetry of financial time series data, the GARCH model can be used to identify volatility (Spulbar, Birau, Jatin, Simion, & Baid, 2023). Examined volatility spillovers in the context of particular Italian and Polish stock markets. The results show that there is high positive volatility between a few selected stock indices. Similarly, (Birău & Trivedi, 2015) & (Birau, Trivedi, & Spulbar, 2021) stock market return data set to conduct empirical tests on CNX 100 volatility clusters; results provide a new understanding of underlying volatility structures. Results indicated the potential for abnormal minor and major shocks, high volatility, and optimistic growth bands.(Ormos & Timotity, 2016). Emphasized the so-called "unprecedented fluctuations" of stock markets in light of global economic dynamics, whereas volatility is associated with stock market uncertainty as well as prospective investor behavior. To estimate and forecast key properties of time series data, multiple models with different variances have been created recently. While there are numerous studies on asymmetric volatility and univariate accuracy testing Models of Generalized Autoregressive Conditional Heterogeneity (Bollerslev, 1986). The authors (Thakolsria, Sethapramote, & Jiranyakul, 2015) & (Agboluaje, Ismail, & Yip, 2016) test the leverage and volatility feedback effects in emerging stock markets, based on modeling two different GARCH parametric asymmetric volatility models using high-frequency trading information from the Thailand Stock Exchange every day. Also, a study used the daily share indices of Germany, Kenya, the United States America, South Africa, and China to estimate asymmetric GARCH models with endogenous break dummies under two unique hypotheses.

Furthermore, studying high-frequency data from over 15 years, (Spulbar & Birau, Modeling and Estimating Long-Term Volatility of Stock Markets in Romania, Poland, Greece, and USA, 2019) looked for evidence of volatility spillovers and patterns, financial contagion, and causal relationships between clusters of stock markets like France, the United Kingdom, the United States, and Canada.(Cristi, Birau, Trivedi, & Mehdiabadi, 2021). Analysed the similarities and differences between the stock markets of two countries with vastly different economies and locations, namely Belgium with its Brussels Stock Exchange and Indonesia with its Jakarta Stock Exchange, using data from January 2018 through September 2021. The primary objective of this study was to use GARCH family models to compare the performance of selected stock markets before and after the COVID-19 pandemic.

There are only a handful of papers that combine high-frequency data and the study of volatility, and among these is an attempt to show that a more accurate assessment of the relationship between volatility and price processes can be made with the help of high-frequency data and the ability of definite stochastic volatility models to analyse the pattern seen in high-frequency data (Litvinova, 2003) & (Khanthavit, 2020), (Okorie & Lin, 2020), (Ashraf, 2020) & (Meher, Hawaldar, Mohapatra, & Sarea, The Impact of COVID-19 on Price Volatility of Crude Oil and Natural Gas Listed on Multi Commodity Exchange of India, 2020). (Higgs & Worthington, 2005) & (Hawaldar, Meher, Kumari, & Kumar, 2022). By including knowledge of latent volatility processes that take place when markets are closed and no transactions take place, some papers have proposed a way to improve volatility modelling (Matei, Rovira , & Agell, 2019) , (Liu, Manzoor, Wang, Zhang, & Manzoor, 2020) & (Onali, 2020). Research was also conducted using the GARCH model to look at natural gas and crude oil price volatility in the United States since 1990. (Pindyck, 2004)&(Chang, McAleer, & Tansuchat, 2012). Also, a study used intraday data from the Gold 5 minutes to compare realized GARCH models with several conventional GARCH models (Hawaldar, Rajesha, & Sarea, Causal Nexus between the Anamolies in the Crude Oil Price and Stock Market, 2020), (Abounoori & Zabol, 2020), (Manera, Nicolini, & Vignati, 2013) & (Mukherjee & Goswami, 2017). Based on an analysis of co-movement among sample stock markets from Asia, Europe, and the USA using the correlation technique, it was found that there was a significant increase in the interdependence between developed and emerging stock markets, particularly when extreme financial events were taking place.

Prior research on economic recessions mostly looked at the crises of the 1980s and 1990s. However, the recent US subprime mortgage crisis has attracted a growing amount of academic interest. Not much research has been done on the emerging markets. Meanwhile, price correlations in SMs have been extensively studied in a variety of settings. Two distinct types of price correlation, spatial and cross-industry, have been identified (Urom, Guesmi , Abid, & Dagher, 2023). The concept of market cointegration, meanwhile, is defined from either an asset pricing or statistical vantage point (Younis, Longsheng, Basheer, & Joyo, 2020). In a cointegrated asset pricing market, investors in a single financial instrument across multiple markets can anticipate achieving the same risk-adjusted returns regardless of where those investors are physically located (Hoq, 2020). When stock prices across the country move in tandem for extended periods of time due to arbitrage or changes in financial regulation, we call this statistical market integration. Increased co-movements and integration between US and Chinese SM exchanges would also reduce the benefits of global portfolio diversification (Czapkiewicz & Wójtowicz, 2017) proposed that the process of interconnection and the generation of both short-term and long-term links between different stock markets around the world are significantly aided by international portfolio diversification and global investors. (Zakoian, 1994) examined the ties between the established German stock market and a number of developing stock markets in Eastern Europe, including the Czech Republic, Poland, Hungary, and Romania, and found evidence of a high degree of integration between some of the studied stock markets.

The data used and analysis methods will be discussed in the following section. The paper concludes with a discussion of the findings and some recommendations for future study.

3. Research Methodology

3.1. Data

In this analysis, we use the time period beginning on January 27, 2000, and ending on March 24, 2023 (daily observations 5605). The final closing prices of stock market indices of USA (S&P 500 Index) and the China (SSE Composite index & HANG SENG index) are collected from www.english.sse.com, www.hsi.com.hk/engand www.reuters.com. The daily continuous compounding returns are used in the present investigation because of their ability to capture fine-grained mode information.

3.2. Methodology

Descriptive statistics were used to examine the overall features and normality of the data set. To use EGARCH, it has been determined whether or not the data is stationary using the ADF (augmented Dickey Fuller test). The concept of Log Daily Returns was developed to standardise non-stationary data. The study used a correlation matrix to look into the connections between different stock exchanges. The purpose of this research is to investigate the dynamic relationship and the association between sample stock markets over the long and short term. We have utilised the (Johansen & Juselius, 1990) test to examine the trend in SM between China and the United States over time. To choose the most appropriate asymmetric volatility model for stock markets, numerous criteria have been used to examine the results of the models after they had been created using different distributions. In addition, the empirical results are significant at levels of 10%, 5%, and 1%, with the 5% significant level being taken into account for the following modelling process. E-Views 10 has applied to the creation of models for certain stock indexes. The following formula is used to determine the continuously-compounded daily returns using the log-difference of the closing prices of the index selected for the stock market:

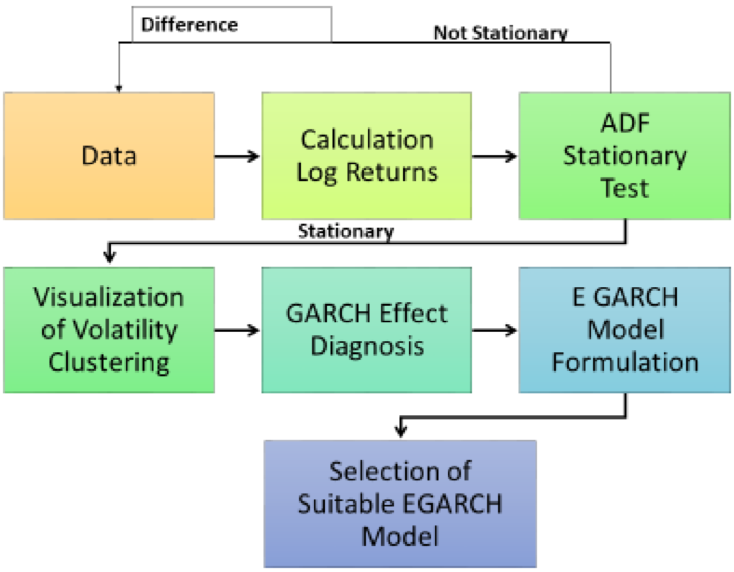
Conversion of Log:

$$y_t = In\_\left(\frac{p_t}{p_{t-1}}\right) = In(p_t) - In(p_{t-1})$$

ADF Process:

$$(1 - L)yt = \beta 0 + (\alpha - 1)yt - 1 + \varepsilon_i$$

3.3 Figure 1 Analysis Process Flow Chart.



4. Empirical Results and Findings

For implementing the GARCH Models the descriptive statistics of all three selected indices are determined which are given in the table 1.

Table 1. Descriptive statistics

	USA S&P	China SSE	China HS
Mean	0.000192	0.000141	0.000261
Median	0.000612	0.000548	0.000295
Maximum	0.109572	0.094008	0.156056
Minimum	-0.12765	-0.09256	-0.15087
Standard Deviation (SD)	0.012469	0.015036	0.018809
Skewness	-0.39112	-0.37238	0.113315
Kurtosis	13.60044	8.295296	9.067641
Jarque- Bera	26385.8**	6678.081**	8610.129**
Observation	5605	5605	5605

** Significant at 1 %,

Source: Own Computations of the Authors using particular financial data series

Table 2. Covariance Analysis/ Correlation Matrix

Sample: 1/27/2000 3/24/2023 (Included observations: 5605)			
Probability	**China (HANG SENG)**	**USA (S&P 500)**	**China (SSE)**
China (HANG SENG)	1.000000		
USA (S&P 500)	0.023274*	1.000000	
	0.0815**	-----	
China (SSE)_	0.026471*	-0.017811*	1.000000
	0.0475*	0.1824**	-----

Source: - authors own computation using EViews 10

In the financial series of the selected index, the standard deviations degree shows 0.012469, 0.012469 (S&P INDEX) 0.015036(SSE) and 0.018809(HSI) relative risks. It is quite notable that the kurtosis indicates a substantially higher degree than the normal**.** Based on the correlation coefficient test, the returns of the selected indices exhibit weak positive correlation, as indicated in Table 2. Furthermore, the values of the coefficients of Skewness, Kurtosis, and Jarque-Bera Statistics confirm that the data of all chosen indices are leptokurtic, or highly peaked.

The presence of the ARCH effect in datasets, a necessary condition of the extended EGARCH model, was verified before the model was used. To keep things straightforward, datasets should have some degree of heteroscedasticity and autocorrelation.

Table 3.Unit Roots Test

Indices	ADF test (t-statistic)	PP test (t-statistic)	ARCH effect (F-statistic)
USA S&P	-83.45771* [0.0001]	-83.50163* [0.0001]	28.32064* [0.0000]
China SSE	-73.48452*[0.0001]	-73.50599* [0.0001]	6.334589 *[0.0119]
China HS	-70.94602*[0.0001]	-70.85249*[0.0001]	0.786945**[0.3751]

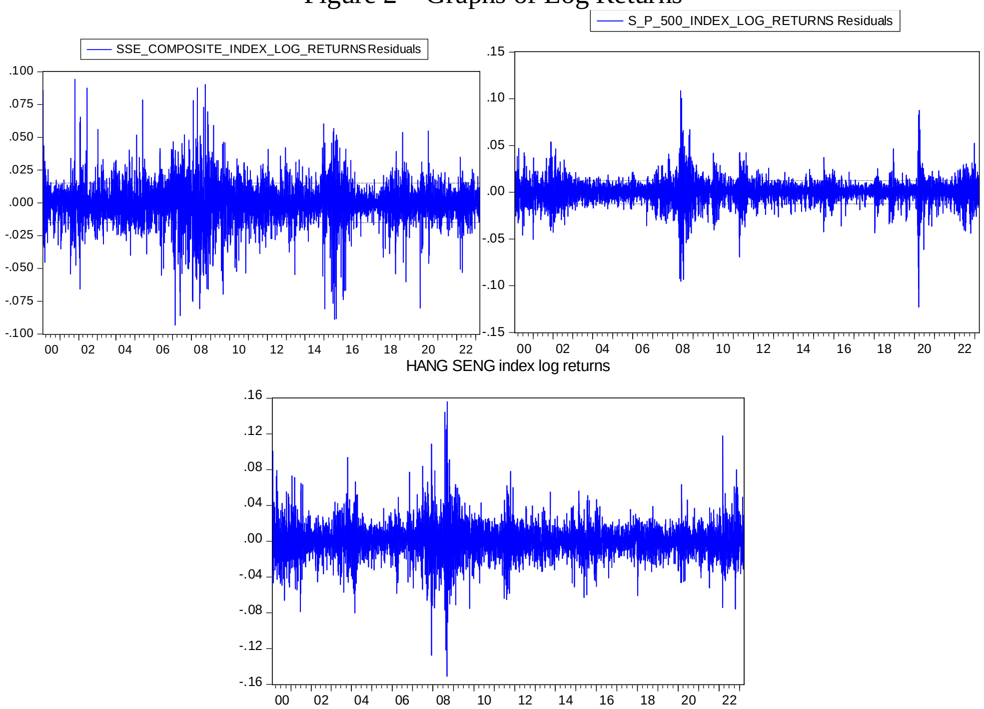
* Significant at level, **Significant at 1 %

Source: - authors own computation using EViews 10

The sample data of the stock prices were again tested for stationarity using the unit root test, or the Augmented Dickey Fuller Test, and Philips Perron test, which includes the test equations Intercept, Trend, and Intercept and none. It was discovered that the sample data are stationary because the probability values are significant at levels of 10%, 5%, and 1%. (Table 3). In addition to verifying the presence of volatility clustering, the ARCH effect must also be present in the data of the chosen financial indices in order to apply EGARCH models. In Table 3, we can see the outcomes of the heteroscedasticity test of stock returns for the chosen indices, which would point to the presence of the ARCH effect in the stock price data.

The following sections are built on evaluating the relevant hypotheses needed to create the EGARCH model. Figure 2 shows graphs with the log returns of the USA and China stock price indexes displayed to show the presence of volatility clustering. Figure no. 2. Movement style of the Stationary Series for IBOVESPA indices for the sample timeframe from 27/01/2000 to 24/ 03/2023.

Figure 2 – Graphs of Log Returns



Source: - authors own computation using EViews 10

The property of Fig 2 indicates there are different clusters in these diagrams because we can see that in Line graphs figure 2, sometimes volatility is high and sometimes volatility is less. After examining the log return graphs of a few selected financial data series in Figure 2, it is clear that the data exhibits volatility clustering, whereby large variations in log returns were followed by equally large differences in log returns, and vice versa. Asymmetric EGARCH models would be suitable for simulating the volatility of the stock prices of a chosen indices.

After determining whether ARCH effects exist, the asymmetric EGARCH model has been developed using five distinct error distribution constructs— Student t's Distribution Error Construct, Normal Distribution Error Construct,Generalized Error Distribution Construct. Student t's Distribution with df and GED with Fixed Parameter Distribution. The leverage effect, which is created because of returns and volatility have a negative correlation, is not captured by the conventional GARCH model since it is asymmetric in nature. The ability of the EGARCH model to capture the leverage effect of shocks like policy, news, information, occurrences, and market events is one of its key selling points.

"The log of the variance distinguishes the EGARCH model from the GARCH variance structure" (Dhamija & Bhalla, 2010). Also, "the advantage of employing EGARCH is that it works with the log of the variance, which ensures the positivity of the parameters" (Hassan, 2012).

The EGARCH model is represented by the following formula.

$$\log(\sigma_t^2) = \omega + \sum_{j-i}^{p} \beta i \log(\sigma_{t-i}^2) + \sum_{j-1}^{q} \alpha i \langle \frac{\varepsilon i - t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| - yi \frac{\varepsilon i - t}{\sigma i - t} \rangle$$

where

log (σ_t^2) *= log of variance or log returns* ω *= Constant*

βi *= Effects of ARCH* αi *= Asymmetric effects*

yi *= Effects OF GARCH*

It is necessary to analyze the outcomes of the developed models with the three distinct distributions in order to select an optimal model. "The standard way to select a model is, the coefficients, ARCH and GARCH should be significant and there should not be existence of Heteroscedasticity and autocorrelation after framing the model. In addition to that, the model with lesser AIC (Akaike Information Criterion) and SIC (Schwartz Information Criterion) is better and a model with higher Log Likelihood statistics, R squared and Adjusted R Squared is better" (Meher, Hawaldar, Mohapatra, & Sarea, The Impact of COVID-19 on Price Volatility of Crude Oil and Natural Gas Listed on Multi Commodity Exchange of India, 2020)**.**

Formulation of EGARCH Models for S&P 500 INDEX of USA

The S&P 500® index is widely accepted as the premier lone indicator of large-cap U.S. equities. An estimated USD 15.6 trillion is indexed or benchmarked to the index, with indexed assets making up roughly USD 7.1 trillion of this total (based on our Annual Survey of Assets) (as of Dec. 31, 2021). The 500 stocks included in the index represent roughly 80% of the available market capitalization (spglobal, 2023)**.**

Table 4: Choosing an appropriate EGARCH (1, 1) model from five distinct error distribution constructs of S&P 500 INDEX (USA) are outlined in the decision table

EGARCH (1,1) Model					
Statistics	Normal Distribution	**Student t's Distribution**	Generalised Error Distributio n	Student t's Distribution	GED with Fixed Parameter
Significant Coefficients	0.0043**	0.0000**	0.0000**	0.0000**	0.0000**
Significant ARCH effects	**	**	**	**	**
Significant GARCH effects	**	**	**	**	**
Log Likelihood	18188.1	**18316.07**	18306.12	18307.70	18298.28
R squared	**0.009095**	0.007855	0.008232	0.008030	0.008307
Adjusted R^2	**0.008918**	0.007678	0.008054	0.007853	0.008130
Akaike info criterion	-6.488992	**-6.534288**	-6.530736	-6.531655	-6.528295
Schwartz criterion	-6.481893	**-6.526005**	-6.522453	-6.524555	-6.521196
Heteroscedasticit y	no	No	No	no	no
Autocorrelation	no	No	No	no	no

** Significant at level

Source: - authors own computation using EViews 10

Table 4 lists the statistical parameters associated with some commonly used asymmetric models, which can be used to help make a model choice. The aforementioned table shows that in all five distinct error distribution constructs of EGARCH (1,1) model, ARCH Effect, GARCH, and the coefficients all have significant values. After constructing the aforementioned models, it was determined that none of the five models had heteroscedasticity (as determined by the ARCH LM Test) or autocorrelation (as determined by the correlogram of residuals and squared residuals). EGARCH with Student t's Distribution has the lowest AIC (**-6.534288**) and SIC (**-6.526005**) when compared to the other four models when the AIC and SIC of all the aforementioned five models are compared. Aside from having the model also has the highest Log Likelihood (19379.63). As a result, this model is thought to be the best one. The table (5) below lists the outcomes of the chosen EGARCH (1,1) Model for the USA S&P index.

Table 5 Results of EGARCH (1,1) with t's distribution error construct USA S&P Index

Dependent Variable: S_P_500_INDEX_LOG_RETURNS				
Method: ML ARCH - Student's t distribution (Marquardt / EViews legacy)				
Sample (adjusted): 1/28/2000 3/24/2023				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)				
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000528	9.69E-05	5.445859	0.0000
S_P_500_INDEX_LOG_RETURNS (-1)	-0.051721	0.013852	-3.733902	0.0002
	Variance Equation			
C(3)	-0.294004	0.024908	-11.80346	0.0000
C(4)	0.145576	0.012950	11.24095	0.0000
C(5)	-0.154274	0.009455	-16.31693	0.0000
C(6)	0.980934	0.002247	436.4581	0.0000
T-DIST. DOF	6.704844	0.543057	12.34649	0.0000
R-squared	0.007855	Mean dependent var		0.000197
Adjusted R-squared	0.007678	S.D. dependent var		0.012466
S.E. of regression	0.012418	Akaike info criterion		-6.534288
Sum squared resid	0.863900	Schwarz criterion		-6.526005
Log likelihood	18316.07	Hannan-Quinn criter.		-6.531401
Durbin-Watson stat	2.113403			

Source: - authors own computation using EViews 10

The EGARCH (1,1) model with the Student t's Distribution Construct was applied to the S&P 500 INDEX of the United States, and the results are shown in Table 5. The findings were separated into two categories. The mean equation is depicted in the upper part, while the variance equation is shown in the lower part. The coefficient of the first lag in the S&P 500 index log returns (-1), as well as the constant (C) in the mean equation, are both significant because their probability values are smaller than 0.05. In case of variance equation, C (3) is the Constant, C (4) is the ARCH coefficient, C (5) is the asymmetric co-efficient and C(6) is the GARCH co-efficient. All the coefficients in the variance equation have probability values of less than 0.05, making them all statistically significant. Moreover, the model has least AIC -6.534288) and SIC (-6.526005) as compared to other relevant models. The value of Log Likelihood is 18316.07 and is higher as compared to the other relevant models. The important point to be focused is the co-efficient of the asymmetric term (λ) is negative i.e., -0.154274 and statistically significant which implies that there is existence of leverage effect on the stock price volatility. Therefore, the variance equation can be illustrated as follows.

$$\log(\sigma_t^2) = -0.2940 + \sum_{j-i}^{p} 0.1455 \log(\sigma_{t-i}^2) + \sum_{j-1}^{q} -0.1542 \left\langle \frac{\varepsilon i - t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| - 0.9809 \, \frac{\varepsilon i - t}{\sigma i - t} \right\rangle$$

Formulation of EGARCH Models for Shanghai Stock Exchange

The largest stock exchange in Chinese mainland is the Shanghai Stock Exchange (SSE). The China Securities Regulatory Commission is in charge of managing this nonprofit institution (CSRC). Stocks, mutual funds, bonds, and derivatives are all traded on the exchange. The Exchange was one of the top exchanges in the world as of the end of November 2022, placing third, fifth, and first in total market capitalization, total turnover, and capital raised, respectively, according to data from the World Federation of Exchanges (WFE)(SSE, 2023)**.**

Table 6: Choosing an appropriate EGARCH (1, 1) model from five distinct error distribution constructs of China SSE is outlined in the Decision Table

	EGARCH model				
Statistics	Normal Distribution	Student t's Distribution	**Generalised Error Distribution**	Student t's Distribution with df	GED with Fixed Parameter
Significant Coefficients	0.4018**	0.0000**	0.0007**	0.0383**	0.0268**
Significant ARCH effects	**	**	**	**	**
Significant GARCH effects	**	**	**	**	**
Log Likelihood	16431.34	16438.49	**16651.33**	16607.94	16609.96
R squared	**0.000339**	0.000048	-0.000443	0.000186	0.000079
Adjusted R^2	**0.000161**	-0.000130	-0.000621	0.000008	-0.000100
Akaike info criterion	-5.862006	-5.864200	**-5.940160**	-5.925032	-5.925754
Schwartz criterion	-5.854906	-5.855917	**-5.931877**	-5.917932	-5.918655
Heteroscedasticity	no	no	No	no	no
Autocorrelation	no	no	No	no	no

** Significant at level Source: **-** authors own computation using EViews 10

The aforementioned table shows that in all five distinct error distribution constructs of EGARCH (1,1) model, ARCH Effect, GARCH, and the coefficients all have significant values. After constructing the aforementioned models, it was determined that none of the five models had heteroscedasticity (as determined by the ARCH LM Test) or autocorrelation (as determined by the correlogram of residuals and squared residuals). EGARCH with Generalized Error Distribution has the lowest AIC (-5.940160) and SIC (-5.931877) when compared to the other four models when the AIC and SIC of all the aforementioned five models are compared. Aside from having the model also has the highest Log Likelihood (16651.33). As a result, this model is thought to be the best one. The table below lists the outcomes of the chosen EGARCH (1,1) Model for the Shanghai Securities Exchange INDEX (China).

Table 7: Results of EGARCH (1,1) model with Generalized Error Distribution of Shanghai Securities Exchange INDEX (China)

Dependent Variable: SSE_COMPOSITE_INDEX_LOG_RETURNS				
Method: ML ARCH - Generalized error distribution (GED) (Marquardt / EViews legacy)				
Sample (adjusted): 1/28/2000 3/24/2023				
Convergence achieved after 17 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5) *RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000428	0.000126	3.397255	0.0007
SSE_COMPOSITE_INDEX_LOG_RETURNS(-1)	-0.001857	0.012292	-0.151096	0.8799
	Variance Equation			
C(3)	-0.237009	0.027673	-8.564693	0.0000
C(4)	0.167530	0.013406	12.49646	0.0000
C(5)	-0.026058	0.007165	-3.637073	0.0003
C(6)	0.987092	0.002706	364.7888	0.0000
GED PARAMETER	1.195337	0.027590	43.32575	0.0000
R-squared	-0.000443	Mean dependent var		0.000138
Adjusted R-squared	-0.000621	S.D. dependent var		0.015035
S.E. of regression	0.015040	Akaike info criterion		-5.940160
Sum squared resid	1.267148	Schwarz criterion		-5.931877
Log likelihood	16651.33	Hannan-Quinn criter.		-5.937274
Durbin-Watson stat	1.958893			

Source: - authors own computation using EViews 10

The Table 7 shows the results of EGARCH (1,1) model with Generalized Error Distribution of Shanghai Securities Exchange INDEX (China). The findings were separated into two categories. The mean equation is depicted in the upper part, while the variance equation is shown in the lower part. In the mean equation the constant (C) is significant as the probability value is less than 0.05. In case of variance equation, C (3) is the Constant, C (4) is the ARCH coefficient, C (5) is the asymmetric co-efficient and C(6) is the GARCH co-efficient. All the coefficients in the variance equation are significant as their probability values are less than 0.05. Moreover, the model has least AIC (-5.940160) and SIC (-5.931877) as compared to other relevant models. The value of Log Likelihood is 16651.33 and is higher as compared to the other relevant models. The important point to be focused is the co-efficient of the asymmetric term (λ) is negative i.e., -0.026058 and statistically significant which implies that there is existence of leverage effect on the stock price volatility. Therefore, the variance equation can be illustrated as follows.

$$\log(\sigma_t^2) = -0.2370 + \sum_{j-i}^{p} 0.1675 \log(\sigma_{t-i}^2) + \sum_{j-1}^{q} -0.0260 \langle \frac{\varepsilon i - t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| 0.9870 \frac{\varepsilon i - t}{\sigma i - t} \rangle$$

Formulation of EGARCH models for the Hang Seng Index (HSI) of China

As the main indicator of Hong Kong's market performance, the Hang Seng Index (HSI) is a free float-adjusted, market capitalization-weighted stock market index. It is the main indicator of Hong Kong's overall market performance and is used to track and record daily changes in the top corporations listed on the Hong Kong Stock Exchange. These 66 component businesses account for approximately 58% of the Hong Kong Stock Exchange's value (HSI, 2023)**.**

Table 8: Choosing an appropriate EGARCH (1, 1) model from five distinct error distribution constructs of China stock index are outlined in the decision table.

	EGARCH model				
Statistics	Normal Distribution	**Student t's Distribution**	Generalised Error Distribution	Student t's Distribution with df	GED with Fixed Parameter
Significant Coefficients	0.000205 [0.2647]	0.000309 [0.0893]	0.000269 [0.1333]	0.000294 [0.1088]	0.000266 [0.1388]
Significant ARCH effects	**	**	**	**	**
Significant GARCH effects	**	**	**	**	**
Log Likelihood	15217.57	**15291.60**	15286.45	15289.45	15286.25
R squared	0.002834	0.002841	0.002821	**0.002850**	0.002828
Adjusted R^2	0.002656	0.002663	0.002643	**0.002672**	0.002650
Akaike info criterion	-5.428827	**-5.454890**	-5.453051	-5.454477	-5.453337
Schwartz criterion	-5.421727	-5.446607	-5.444768	**-5.447377**	-5.446237
Heteroscedasticity	no	no	no	No	No
Autocorrelation	no	no	no	No	No

The aforementioned table shows that in all three EGARCH (1,1), three TGARCH (1,1), and three MGARCH (1,1) models with normal distribution error construct, student t's distribution error construct, and Generalized error distribution construct, the coefficients, ARCH Effect, and GARCH are significant. After constructing the aforementioned models, it was determined that none of the nine models had heteroscedasticity (as determined by the ARCH LM Test) or autocorrelation (as determined by the correlogram of residuals and squared residuals). EGARCH with Student t's Distribution has the lowest AIC (-**5.454890**) and SIC (-5.446607) when compared to the other five models when the AIC and SIC of all the aforementioned six models are compared. Aside from having,this model also has the highest Log Likelihood (**15291.60**). As a result, this model is thought to be the best one. The table below lists the outcomes of the chosen EGARCH (1,1) model for the China HIS index.

Table 9. Results of EGARCH (1,1) with Student's t distribution Error Construct

Dependent Variable: HANG_SENG_INDEX_LOG_RETURNS				
Method: ML ARCH - Student's t distribution (Marquardt / EViews legacy)				
Sample (adjusted): 1/28/2000 3/24/2023				
Convergence achieved after 14 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5) *RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000309	0.000182	1.699184	0.0893
HANG_SENG_INDEX_LOG_RETURNS(-1)	0.050957	0.013774	3.699537	0.0002
Variance Equation				
C(3)	-0.238030	0.027970	-8.510212	0.0000
C(4)	0.157427	0.013065	12.04944	0.0000
C(5)	-0.037543	0.007448	-5.040527	0.0000
C(6)	0.985796	0.002769	356.0441	0.0000
T-DIST. DOF	7.965126	0.855898	9.306166	0.0000
• R-squared	0.002841	Mean dependent var		0.000261
• Adjusted R-squared	0.002663	S.D. dependent var		0.018810
• S.E. of regression	0.018785	Akaike info criterion		-5.454890
• Sum squared resid	1.976857	Schwarz criterion		-5.446607
• Log likelihood	15291.60	Hannan-Quinn criter.		-5.452004
• Durbin-Watson stat	1.992180			

Source Authors computation

The Table 9 shows the results of EGARCH (1,1) model with Student t's Distribution Construct for Hang Seng Index of China. The results classified in two parts. The upper part shows the mean equation, and the lower part represents the variance equation. In the mean equation the constant (C) is significant as the probability value is less than 0.05 and even the co-efficient of first lag HANG_SENG_INDEX_LOG_RETURNS (-1) is also significant as its probability value is also less than 0.05. In case of variance equation, C (3) is the Constant, C (4) is the ARCH coefficient, C (5) is the asymmetric co-efficient and C(6) is the GARCH co-efficient. All the coefficients in the variance equation are significant as their probability values are less than 0.05. Moreover, the model has least AIC (-5.454890) and SIC (-5.446607) as compared to other relevant models. The value of Log Likelihood is 15291.60 and is higher as compared to the other relevant models. The important point to be focused is the co-efficient of the asymmetric term (λ) is negative i.e., -0.037543 and statistically significant which implies that there is existence of leverage effect on the stock price volatility. Therefore, the variance equation can be illustrated as follows.

$$\log(\sigma_t^2) = -0.2380 + \sum_{j-i}^{p} 0.1574 \log(\sigma_{t-i}^2) + \sum_{j-1}^{q} -0.0375 \langle \frac{\varepsilon i - t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| 0.9857 \frac{\varepsilon i - t}{\sigma i - t} \rangle$$

Table 10: Cointegration between the USA and China

Trend assumption: Linear deterministic trend						
Series: HANG_SENG_INDEX_LOG_RETURNS S_P_500_INDEX_LOG_RETURNS SSE_COMPOSITE_INDEX_LOG_RETURNS						
Lags interval (in first differences): 1 to 4						
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.191663	3196.091	29.79707	1191.550	21.13162	1.0000
At most 1 *	0.170740	2004.541	15.49471	1048.440	14.26460	1.0000
At most 2 *	0.156953	956.1013	3.841466	956.1013	3.841466	0.0000
Trace test indicates 3 cointegrating eqn(s) at the 0.05 level						
* denotes rejection of the hypothesis at the 0.05 level						

Source – Author's computation

Based on output of the Johansen's test of series of log returns value of Hang Seng Index, S&P500 index and SSE Composite Index, the trace value(3196.091) is greater than the critical value at 0.05(29.79707).So in this case we are rejecting the null hypothesis i.e. three is no cointegration equation in this model. Taken the look of Max-Eigen value our decision is not different from, what we made on the trace value. Max-Eigen value (1191.550) is also greater than the critical value at 0.05 (21.13162). Results implies that there is long term relationship among the variables and they can combine in a liner fashion. It also implies that if there are shocks in the short run, which may affect the movement in the individual series, they would coverage with time (in the long run).

Above statement can also be justified by the outcomes from the Bounds cointegration test. Here the value of F-statistics is more them the critical value for the upper bound *I*(1), then we can conclude that there is cointegration.

Table 11. F-Bounds cointegration Test

F-Bounds cointegration Test				
Null Hypothesis: No levels relationship				
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	**1261.548**	10%	**2.63**	**3.35**
k	2	5%	3.1	3.87
		2.5%	3.55	4.38
		1%	4.13	5

Source – Author's computation

5. Conclusions

The purpose of the study is to examine and provide an explanation for the short- and long-term integration of the US and China from 2000 to 2023. To look into how the US and Chinese markets have developed over time during particular time periods, the (Johansen & Juselius, 1990) cointegration is used. The study's findings demonstrate that the Chinese and American markets are intertwined over long periods of time. The trace value and Max- Eigen value is bigger than the crucial value at 0.05 based on the results of the Johansen's test of a series of log returns values of the Hang Seng Index, S&P500 Index, and SSE Composite Index. Hence, we reject the null hypothesis in this situation, i.e., there is no cointegration equation in this model. The results indicate that the factors have a long-term association and can be combined in a liner form. It also means that if there are short-run shocks that alter the movement in the individual series, they will be covered over time (in the long run). The results of the EGARCH model confirmed that there were occasionally asymmetric volatility spillover effects between the US and Chinese markets. The fact that the two markets have a statistically significant bidirectional spillover demonstrates the tenuous relationship between them. The current study's goal is to analyse co-movement within China, and it does so by laying a solid technical foundation on which to see how the variables interact in the sample at hand. These results are crucial for the current investment behaviour of investors in terms of diversification prospects. For a wide range of stakeholders, including investors and government policymakers, the current study has several beneficial practical implications. The study's findings are significant for all parties involved, especially policymakers in the Chinese market. Who might be better able to create and carry out policies, particularly in the area of economic policy? Future researchers can explore the transmission channels that aided the crisis's spread throughout local and regional economies to expand the concept. The current work would also act as a springboard for additional investigations into cointegration and volatility spillovers.

References:

Czapkiewicz, A., & Wójtowicz, T. (2017). Spatial contagion between stock markets in Central Europe. *Managerial Economics, 18*(1), 23-44. doi:https://doi.org/10.7494/manage.2017.18.1.23

Abounoori, E., & Zabol, M. A. (2020). Modeling Gold Volatility: Realized GARCH Approach. *24*(1), 299-311. doi:10.22059/ier.2020.74483

Agboluaje, A. A., Ismail, S. B., & Yip, C. Y. (2016, March 15). Research Article Modeling the Asymmetric in Conditional Variance. *Asian Journal of Scientific Research, 9*(2), 39-44. doi:10.3923/ajsr.2016.39.44

Ali, G. (2013). EGARCH, GJR-GARCH, TGARCH, AVGARCH,NGARCH, IGARCH and APARCH Models for Pathogens at Marine Recreational Sites. *Journal of Statistical and Econometric Methods, 2*(3), 57-73.

Almeida, D. d., & Hotta, L. K. (2014, August). THE LEVERAGE EFFECT AND THE ASYMMETRY OF THE ERROR DISTRIBUTION IN GARCH-BASED MODELS: THE CASE OF BRAZILIAN MARKET RELATED SERIES. *Pesquisa Operacional, 34*(2). Retrieved from https://www.scielo.br/scielo.php?script=sci_arttext&pid=S0101-74382014000200237

Alper, C. E., Fendoglu, S., & Saltoglu, B. (2009). MIDAS Volatility Forecast Performance Under Market Stress: Evidence from Emerging and Developed Stock Markets. *Working Papers 2009/04, Bogazici University, Department of Economics*.

Ashraf, B. N. (2020, May). Stock markets' reaction to COVID-19: cases or fatalities? *Research in International Business and Finance*, 1-18. doi:https://doi.org/10.1016/j.ribaf.2020.101249

Birau, R., Trivedi , J., & Spulbar , C. (2021). Estimating Volatility and Investment Risk: An Empirical Case Study for NIFTY MIDCAP 50 Index of National Stock

Exchange (NSE) in India. *Ovidius" University Annals, Economic Sciences Series, XXI*,(I), 691-697. Retrieved from https://www.researchgate.net/publication/354325749_Estimating_Volatility_and_Investment_Risk_An_Empirical_Case_Study_for_NIFTY_MIDCAP_50_Index_of_National_Stock_Exchange_NSE_in_India?enrichId=rgreq-d68c9143aefe850222c417eb2cbe1b21-XXX&enrichSource=Y292ZXJ

Birăua, R., & Trivedib, J. (2015). Estimating long-term volatility on National Stock Exchange of India. *Procedia Economics and Finance*, 574 – 579. doi:doi: 10.1016/S2212-5671(15)01434-3

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327.

Chang, C.-L., McAleer, M., & Tansuchat, R. (2012, December). Modelling Long Memory Volatility. *Annals of Financial Economics, 7*(2), 1-27. doi:10.1142/S2010495212500108

Choudhary, S. (2020, June 15). *COVID-19 and the Indian power sector: Effects and Revival*. Retrieved from www.investindia.gov.in: https://www.investindia.gov.in/team-india-blogs/covid-19-and-indian-power-sector-effects-and-revival

Cristi, S., Birau, R., Trivedi, J., & Mehdiabadi, A. (2021). Modelling volatility spillovers, cross-market correlation and co-movements between stock markets in European Union: an empirical case study. *Business, Management and Economics Engineering, 9*(1), 70-90. doi:http://dx.doi.org/10.3846/bmee.2021.13588

Dedi, L., Yavas, B. F., & McMillan, D. (2016). Return and volatility spillovers in equity markets: An investigation using various GARCH methodologies. *Cogent Economics & Finance, 4*(1). doi:https://doi.org/10.1080/23322039.2016.1266788

Dhamija, A. K., & Bhalla, V. K. (2010). Financial Time Series Forecasting: Comparison of Neutral Networks and ARCH Models. *International Research Journal of Finance of Management, 49*(1), 159-172.

Engle, R. F. (1986). Modelling the persistence of conditional variances. Econometric Reviews. *Econometric Reviews*, 5-1-50.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). Relationship between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779-1801.

Gunay, S. (2020, April). A NEW FORM OF FINANCIAL CONTAGION: COVID-19 AND STOCK MARKET. *Working Paper*.

Hailemariam, A., & Smyth, R. (2019, February). What Drives Volatility in Natural Gas Prices? *Energy Economics*, 1-31. doi:10.1016/j.eneco.2019.02.011

Harvey, A., & Sucarrat, G. (2014). EGARCH models with fat tails, skewness and leverage. *Computational Statistics and Data Analysis, 76*(1), 320-338. doi:10.1016/j.csda.2013.09.022

Hassan, E. (2012, August). The Application of GARCH and EGARCH in Modeling the Volatility of Daily Stock Returns During Massive Shocks: The Empirical Case of Egypt. *International Research Journal of Finance and Economics*(96), 153-165.

Hawaldar, I. T., Meher, B. K., Kumari, P., & Kumar, S. (2022, March 30). Modelling the effects of capital adequacy, credit losses, and efficiency ratio on return on assets and return on equity of banks during COVID-19 pandemic". *Banks and Bank Systems, 17*(1), 115-124. doi:http://dx.doi.org/10.21511/bbs.17(1).2022.10

Hawaldar, I. T., Rajesha, T. M., & Sarea, A. M. (2020, February). Causal Nexus between the Anamolies in the Crude Oil Price and Stock Market. *International Journal of Energy Economics and Policy, 10*(3). doi:https://doi.org/10.32479/ijeep.9036

Higgs, H., & Worthington, A. C. (2005, October). Systematic Features of High-Frequency Volatility in Australian Electricity Markets: Intraday Patterns, Information Arrival and Calendar Effects. *The Energy Journal, 26*(4), 23-41. doi:10.5547/ISSN0195-6574-EJ-Vol26-No4-2

Hoq, M. E. (2020). Co-Integration Approach: Relationship between Asia-Pacific and USA Stock Markets during the Financial Crisis of 2008? An Empirical Study. *AIUB Journal of Business and Economics, 17*(1), 109-128. Retrieved from file:///C:/Users/HP/Downloads/AJBE_17_1_6.pdf

HSI. (2023). *Hang Seng Indexes* . Retrieved from https://www.hsi.com.hk/eng/about-us/company-profile

Johansen, S., & Juselius, K. (1990). MAXIMUM LIKELIHOOD ESTIMATION AND INFERENCE ON COINTEGRATION — WITH APPLICATIONS TO THE DEMAND FOR MONEY. *Oxford Bulletin of Economics and Statistics, 52*(2), 169-210. Retrieved from https://onlinelibrary.wiley.com/doi/10.1111/j.1468-0084.1990.mp52002003.x

Khanthavit, A. (2020, May). World and National Stock Market Reactions to COVID-19. doi:10.13140/RG.2.2.22792.57606

Kilian, L. (2008). . Exogenous oil supply shocks: how big are they and how much do they matter for the US economy? *Review of Economics and Statistics, 90*(2), 216-240. Retrieved from https://econpapers.repec.org/article/tprrestat/v_3a90_3ay_3a2008_3ai_3a2_3ap_3a216-240.htm

Litvinova, J. (2003, February 13). Volatility Asymmetry in High Frequency Data. *Debt Washington,* 1-38. Retrieved from http://depts.washington.edu/sce2003/Papers/204.pdf

Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020, April 18). The COVID-19 Outbreak and Affected Countries Stock Markets Response. *International Journal of Environmental Research and Public Health, 17*, 1-19. doi:https://dx.doi.org/10.3390/ijerph17082800

Manera, M., Nicolini, M., & Vignati, I. (2013, April). Futures price volatility in commodities markets:The role of short term vs long term speculation. *DEM Working Paper Series*.

Matei, M., Rovira , X., & Agell, N. (2019, September 15). Bivariate Volatility Modeling with High-Frequency Data. *Econometrics, 7*(41), 1-15. doi:10.3390/econometrics7030041

Meher, B. K., Hawaldar, I. T., Mohapatra, L., & Sarea, A. (2020). The Impact of COVID-19 on Price Volatility of Crude Oil and Natural Gas Listed on Multi Commodity Exchange of India. *International Journal of Energy Economics and Policy | Vol 10 • Issue 5 • 2020, 10*(5), 422-431. doi:https://doi.org/10.32479/ijeep.10047

Meher, B. K., Hawaldar, I. T., Mohapatra, L., & Sarea, A. M. (2020, July 1). The Impact of COVID-19 on Price Volatility of Crude Oil and Natural Gas Listed on Multi

Commodity Exchange of India. *International Journal of Energy Economics and Policy, 10*(5), 1-10. doi:https://doi.org/10.32479/ijeep.8559

Mukherjee, I., & Goswami, B. (2017). The volatility of returns from commodity futures: evidence from India. *Financial Innovation, 3*(15), 1-23. doi:10.1186/s40854-017-0066-9

Narayan, P., Sharma, S., Poon, W., & Westerlund, J. (2014). Do oil prices predict economic growth? New global evidence. *Energy Economics, 41*, 137-146.

Okorie, D. I., & Lin, B. (2020, June). Stock Markets and the COVID-19 Fractal Contagion Effects. *Finance Research Letters*. doi:https://doi.org/10.1016/j.frl.2020.101640

Onali, E. (2020, May 28). Covid-19 and stock market volatility. *Journal of Business Finance & Accounting, 41*(2), 128-155.

Ormos, M., & Timotity, D. (2016). Unravelling the Asymmetric Volatility Puzzle: A Novel Explanation of Volatility Through Anchoring. *Economic Systems*, 1-26. doi:10.1016/j.ecosys.2015.09.008

Pavlyshenko, B. M. (2020, April). Regression Approach for Modeling COVID-19 Spread and Its Impact On Stock Market. 1-10.

Peter, H. R., Huang, Z., & Shek, H. H. (2012, August). Realized GARCH: A Joint Model for Returns and Realized Measures of Volatility. *Journal of Applied Econometrics, 21*(1), 1-21. doi:10.1002/jae.1234

Pindyck, R. S. (2004). Volatility in Natural Gas and Oil Markets. *The Journal of Energy and Development, 30*(1), 1-20.

Raja Ram, A. (2020, April 21). *COVID-19 and stock market crash*. Retrieved from www.outlookindia.com: https://www.outlookindia.com/outlookmoney/equity/covid-19-impact-on-stock-market-4666

spglobal. (2023). *S&P Dow John indices*. Retrieved from https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview

Spulbar, C., & Birau, R. (2019). Modeling and Estimating Long-Term Volatility of Stock Markets in Romania, Poland, Greece, and USA. *Emerging Research on Monetary*, 198-214. doi:10.4018/978-1-5225-9269-3.ch009

Spulbar, C., Birau, R., Jatin, T., Simion, M. L., & Baid, R. (2023). Assessing Volatility Patterns using GARCH Family Models: A Comparative Analysis Between the Developed Stock Markets in Italy and Poland. *Annals of "Dunarea de Jos" University of Galati Fascicle I. Economics and Applied Informatics*, 1-11. doi:https://doi.org/10.35219/eai15840409314

Spulbar, C., Trivedi, J., & Birau, R. (2020). Investigating abnormal volatility transmission patterns between emerging and developed stock markets: A case study. *Journal of Business Economics and Management, 21*(6), 1561-1592. doi:https://doi.org/10.3846/jbem.2020.13507

SSE. (2023). *Shanghai Securities Exchange*. Retrieved from http://english.sse.com.cn/aboutsse/overview/

Thakolsria, S., Sethapramote, Y., & Jiranyakul, K. (2015, October). Asymmetric volatility of the Thai stock market: evidence from highfrequency data. *Munich Personal RePEc Archive, MPRA Paper No. 67181*, 1-7. Retrieved from https://mpra.ub.uni-muenchen.de/67181/

Urom, C., Guesmi , K., Abid, I., & Dagher , L. (2023). Dynamic integration and transmission channels among interest rates and oil price shocks. *The Quarterly*

Review of Economics and finance, 87, 296-317. doi:https://doi.org/10.1016/j.qref.2021.04.008

Uyaebo, S. O., Atoi, V. N., & Usman, F. (2015, December). Nigeria Stock Market Volatility in Comparison with some Countries: Application of Asymmetric GARCH Models. *CBN Journal of Applied Statistics, 6*(2), 133-160. doi:http://hdl.handle.net/10419/142109

Younis, I., Longsheng, C., Basheer, M. F., & Joyo, A. S. (2020). Stock market comovements among Asian emerging economies: A wavelet-based approach. *PLoS ONE 15(10): e0240472*. doi:https://doi.org/10.1371/journal.pone.0240472

Zakoian, J.-M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control, 18*(5), 931-955. doi:https://doi.org/10.1016/0165-1889(94)90039-6

Authors' Contributions

The authors contributed equally to this work.

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