



EXAMINING THE CONTEMPORANEOUS CAUSALITY BETWEEN CHINESE AND GHANAIAN STOCK MARKETS AMIDST THE COVID-19 PANDEMIC

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ABSTRACT

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Examining the contemporaneous causality between Chinese and Ghanaian stock markets before and amidst the coronavirus disease 2019 (COVID-19) pandemic is of immense interest to many stakeholders in making effective and efficient decisions. This study investigates why the two stock markets' fluctuations seem to move in tandem despite a broader economic phenomenon. Shanghai Stock Exchange and Ghanaian Stock Exchange composite indices data were used for this study spanning 2011 - 2020. The Granger causality and transfer entropy are applied to investigate the mean transmission. The Dynamic Conditional Correlation - Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) model portrays the dynamic correlation and the ARMA model is used to fit the log-returns of the two indices. Results show that the Chinese stock market has a substantial causal effect on the Ghanaian stock market based on transfer entropy with the second-order of lag while there is a considerable causality from the stock market of Ghana to the Chinese stock market through the third and fifth orders of lags. This implies the asynchronous return transmission between Chinese and Ghanaian stock markets. Moreover, the long-term volatility connection significantly impacts the two markets, but the short-term volatility pattern does not heavily affect the markets based on the DCC-GARCH model. The best-fitted model for the log-returns of two stock markets is ARMA (1,1). This study recommends that policymakers and investors adopt diversification as a resort to financial management.

KEYWORDS: COVID-19; stock returns; causality; Ghana stock exchange; Shanghai stock exchange; composite index.

1. INTRODUCTION

The sensitive role of stock markets as one of the most pivotal financial instruments highly monitored by economists and policymakers to track economic development, commerce and raise funds for expansion in a country cannot be underestimated. Stock indexes are among the most closely monitored asset indexes in the economy and are commonly regarded as highly sensitive to economic conditions (Machado, Saraiva & Vieira 2021). Examining the statistical link and dynamics of stock volatility and return movement in China and Ghana before and during the COVID-19 Pandemic is worth studying to determine the pattern of volatility and market performance. The financial system of China and Ghana comprise all financial markets, instruments, and institutions. The two financial markets' current performance and volatility are the key reasons that aroused the researchers' interest to make it relevant to examine the contemporaneous causality between the two emerging countries' stock markets before and during the COVID-19 Pandemic. This study's primary motivation is to determine the mean and volatility transmission effect on these exchanges from the period 2011.10.14 through 2020.09.18. The significance of this study is to help the Chinese and Ghanaian stock markets participants to take a critical look at the effect of the transmission in mean and volatility amidst unforeseen circumstances such as the COVID-19 Pandemic and financial contagion periods that generate enormous repercussions on the two economies stock markets performance. A reflection of the unexpected event that caused fluctuation in both economies and the world could be traced to the financial contagion era of the 2007/2008 American crisis that could be likened to the current COVID-19 contagion.

The COVID-19 disease is an emerging illness caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (Lu et al. 2020; Zhou et al. 2020). The emergence of this Pandemic has posed a significant challenge to all humanities and enterprises globally, especially the stock markets. The apocalyptic nature of the COVID-19 has made many economies experience increasing levels of financial contagion, mass unemployment, and reduction in gains for several industries in the globe without any severe shortcomings in their respective economies. Many industries are shutting down because of the mandatory stay-at-home policies imposed by the countries they do business. The global value chain has already been severely disrupted as a result of the reliance on intermediate goods from countries affected by international trade. The essential commodities production companies that are still operating amid the COVID-19 Pandemic have two options: either their workers have had to face the challenge of protecting their lives or livelihoods, or they have had to choose between the two. Because the fear of losing their lives in the COVID-19 is a terrifying prospect, a large number of workers choose their lives over livelihoods that sound more appealing (Gyeke-Dako, Vera & Saint 2020).

The heightening of cases and the effect of the COVID-19 on the global economies and livelihoods has made the global leaders take different measures to ensure safety and socio-economic resilience. Aside from international measures that are being implemented by all and sundry. These two countries' governments have implemented a series of steps and updates to ensure their citizens' safety and their economies amidst the rise of the COVID-19 Pandemic. The recent State of the Nation's address issued by the Government of Ghana on his 23rd Update regarding measures taken against the spread of COVID-19 indicates the country's turbulence period in the battle against the COVID-19 Pandemic. *The rising of the COVID-19 is evidenced in our hospitals. Our hospitals are overburdened, and we have had to reactivate our isolation centers. Our average daily rates of*

infection now stand at seven-hundred (700), compared to two hundred (200) two weeks ago (Graphic.com.gh 2021)

The Chinese government has been working hard to avoid and monitor the COVID-19 while maintaining a high degree of accountability (Wu & McGoogan 2020). China and the world at large in the turbulence of the COVID-19 have been implementing measures and launching a slew of vaccine campaigns in the hopes of putting an end to the coronavirus pandemic that has lasted a year (Shanghai-Reuters 2020). However, the various vaccines and other medications produced to curb the situation have not yielded the maximum results expected. Hence the disease continues to resurface in a different form currently ascribed as the Variant of SARS-COV-2 virus with standard change N501Y mutation, which was earlier seen in the United Kingdom and South Africa.

There is evidence that the surge of the COVID-19 Pandemic with its economic impact has dramatically affected the global markets, not excluding the Shanghai Stock Exchange (SSE) in China and the Ghanaian Stock Exchange (GSE) in Ghana. For international securities investors seeking diversification advantages, these two emerging markets have been popular destinations (Vo & Ellis 2018). When global economic policy uncertainty is high, information transfer's asymmetric impact tends to make the stock market a surrogate for international securities diversification (Adam 2020). Stock markets serve as an engine for growth for economies. A growing trend of global and regional trade agreements among countries has preceded increased financial integration (Balli, Hajhoj, Basher & Ghassan 2015).

In essence, there is a growing perception that return and volatility transmission can limit global diversification; understanding foreign information transmission mechanisms can lead to predicting an internal market's behavior using international data. As a result, evaluating bidirectional return and volatility spillovers between the Shanghai and Ghanaian stock markets is critical for understanding international information transmission channels and developing effective trading strategies. This paper's empirical findings will provide factual information on nature, current performance, and the two markets' volatility trend to investors, financial analysts, policymakers, and governments to make operational decisions when investing and diversifying in turbulent periods. This paper is the first to look into the possibility of contemporaneous causality between two emerging stock markets before and during the unprecedented COVID-19 Pandemic. Finally, this study also adds to the literature and innovatively used the ARMA, GARCH, Granger Causality, Transfer Entropy, and DCC GARCH models to ascertain results' dynamics and accuracy.

2.0 THEORETICAL BACKGROUND

This study's primary literature focused on transmitting stock composite indices' returns and volatility and literary works from the COVID19 era.

2.1 Volatility clustering of SSE and GSE

Financial time series typically exhibit a set of traits, according to univariate models of conditional volatility. Stock market returns often show "volatility clustering," which occurs when significant changes in returns are followed by another large difference for an extended period, and small changes are followed by minor changes for an extended period (Ning, Xu & Wirjanto 2015; Ausin, Galeano & Ghosh 2014; Poon & Granger 2003) leading to conterminous periods of volatility and stability. The time series exhibits autoregressive conditional heteroskedasticity when the clustering is large (Poon, Leung & Lee 2002). The higher the frequency of the sample data, the more pronounced the effect becomes. The impact of volatility clustering is that past, and current fluctuations can predict future volatility. The ARCH model was used by Ning et al. (2015) to capture volatility persistence and found a close relationship between clustering and thick tails. The presence of non-normal asset distribution can be attributed to the excess kurtosis.

Finance theories indicate that risk and return should have positive relations implying that an increased risk should correspond to an increase in expected returns. Nevertheless, due to unforeseen circumstances, this theorem in practice sometimes does not hold good. The term 'return' indicates the rate of variation between two time periods in the value of an investment, and 'risk' is the potential volatility or variability in that return. Stock returns are unique from other types of investments because of the implication of the continuous compounding concept (Hussain, Bhanu Murthy & Kumar Singh 2019). This characteristic of stock return requires its measurement from a natural logarithmic scale. If r_t denotes the stock return at time t and p_t represents the stock price at time t , the stock's logarithmic return can be written as:

$$\ln r_t = \log(P_t) - \ln(P_{t-1}) \text{ or else } \ln r_t = \log(P_t/P_{t-1}) \quad (1)$$

where P_t and P_{t-1} indicate the index at the end of day t .

When stock returns are fragmented daily, the dividend component is mostly not captured at this stage solely for being insignificant. The movement of returns for these two markets is appropriate to depict the series in Figures 1 and 2, which can be observed that volatility changes over time tend to cluster stock returns, which

is an indicator for extended memory. The plots also show that these two-stock market returns' volatilities have a volatility clustering characteristic during the sample period and have some distinct features in their return volatility procedures. As the fluctuation of the SSE return index grew more extensive, the Volatility of GSE returns also exhibit similar characteristics. The returns fluctuate around their mean value near zero, and the variance indicates volatility clustering. The observations, once again, show consistent fluctuations that are high for some periods and low for others. Thus, serving as the primary motive for studying and discussing the contemporaneous causality of stock index returns between the GSE and SSE. RGSE represents the GSE composite index's logarithm, while RSSE also denotes the SSE composite index's logarithm.

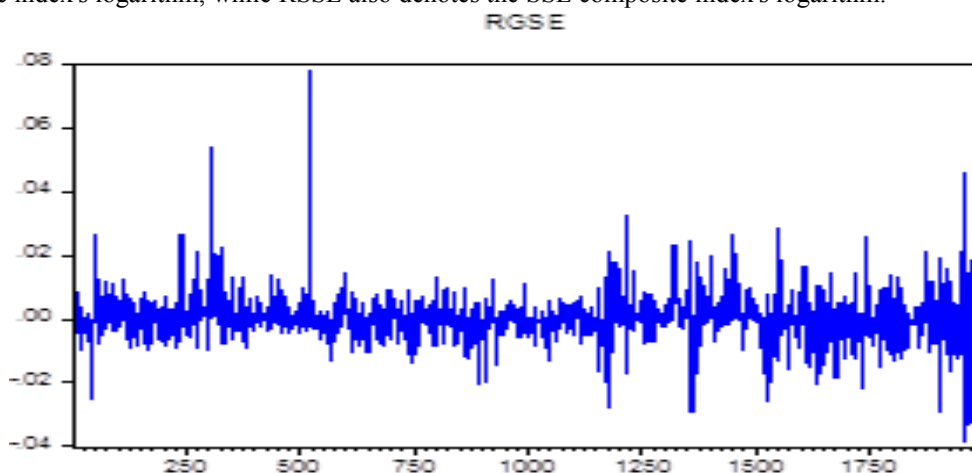


Figure 1 RGSE plot of composite index return data series and volatility clustering

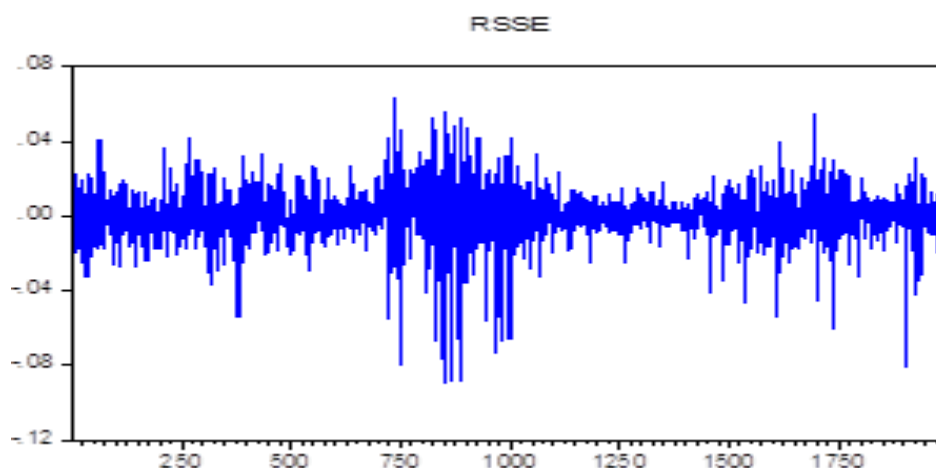


Figure 2 RSSE plots of composite index return data series and volatility clustering

The relationship between economic variables and stock markets is, of course, attractive considering the importance of stock markets in financial industry stability to promote a country's economic development (Myovella, Karacuka & Haucap 2020). The stock market is critical to economic prosperity, capital formation, and long-term economic growth (Al-Tamimi, Alwan & Abdel Rahman 2011; Adjasi, Harvey & Agyapong 2008). The stock market is one of the most important aspects of a free market economy because it helps businesses organize capital by allowing shareholders to trade shares of ownership for cash (M'rabet & Boujjat 2016). The wealth of shareholders and their expectations for future profits are primarily determined by market-based indicators (Dreyer, Viviers & Mans-Kemp 2021).

2.2 Effects of Leverage

When the previous day's returns are negative, the leverage effect causes volatility to rise. Stock price changes are inversely proportional to stock volatility changes (Dana 2016). When a company's stock price falls, it increases its leverage and financial risk due to outstanding debt and equity. The volatility of stocks has an essential beneficial connection with financial leverage and interest rates (Adkins, Cooper & Konings 2019).

2.3 Empirical Studies on Stock Exchange Volatility

Macroeconomic fundamentals influence stock market volatility in various ways, which is more pronounced during recessions (Ellington 2018). The COVID-19 events make the stock markets volatile. Many investors are shifting their wealth away from equity and private bond markets and toward government bonds, cash, and other safe assets like gold, which appear to be better and safer in the current environment. Currently, the outbreak is having an unprecedented impact on the volatility of many stock markets (Baker et al. 2020). As a result of the COVID-19 Pandemic's turbulence, several companies have declared bankruptcy or entered voluntary administration (Virgin-Australia 2020). Numerous companies face a dire need of financial phenomena, especially companies with insufficient liquidity have resorted to the stock exchanges to raise funds to cushion the company's liquidity and equity status.

The COVID-19's socio-economic effect increased food prices, economic hardships related to the lockdown directive, and mandatory relocation and decongestion activities to impose social distancing among merchants operating in the market places (Asante & Mills 2020). As China seems not recovering to the new normal, the seriousness of the effect of the COVID-19 is heavily felt by Ghanaian traders as it is perceived as the seventh-largest trading partner of China in Africa. Ghanaian traders fear running out of stock Kaledzi, (2020) due to the restrictions on specific transactions and traveling policies as the surge of the COVID-19 continues. Thousands of enterprises and traders in the West African countries rely heavily on China's commodities to serve millions of consumers. However, the surge of the COVID-19 in China means that traders cannot access goods to survive in business.

Initially, there was a statistically insignificant negative relationship between the COVID-19 Pandemic and Ghanaian stock market returns. However, the final results show that the COVID-19 Pandemic has caused an 8.23% increase in the volatility of Ghana stock returns (Michael, Lilian, Samuel & Kwaw 2021). The persistence of the COVID-19 outbreak could further weigh on investors' risk appetite, thereby impacting the stock market and bond market (Larbi-Odam, Awuah & Frimpong-Kwakye 2020). Takyi & Ennin (2020) found that stock exchanges' return in Africa has significantly reduced after the first section of the COVID-19 Pandemic, usually between -2.7% and -21%. An indication that COVID-19 has had a restrictive effect on Ghana and Africa as a whole. The global financial markets and the economy of the "world's factory" have been adversely impacted by the outbreak of the novel coronavirus disease COVID-19 (Statista 2021).

ARCH methods have been extensively used in studies of investment and financial market volatility, so their existence is well known and extended to many stock market data sets (Lin 2018). The unrestricted probability distributions of financial returns are leptokurtic, and a stylized trait is known long before ARCH models appeared. In contrast to the normal distribution, they have fatter tails and far more weight around the mean (Chkili & Nguyen 2014). With daily and weekly data on the volume or quality of the data reaching the markets, or between information arrival and dissemination by market players, ARCH effects are highly important (Sévi 2014). However, the effects weaken when the information's frequency decreases (Xie & Huang 2014).

China has been strengthening its ties with Africa and growing its trade and investment in the region. As long as it has a considerable investment in 46 of the 54 countries, the Chinese financial market now significantly influences African stock markets. This suggests a vital portfolio management implication as a surge in Chinese investments provides new portfolio diversification opportunities for international investors. This has essential asset management ramifications, as an increase in Chinese securities gives future markets for foreign investors to improve their investments. Considering the increasing literature on China's and Ghana's stock market performance, empirical evidence on the two stock markets' return and volatility characteristics are largely lacking. Hence, this study aims to fill this gap.

3. DATA AND METHODOLOGY

It assumes that financial market studies compete to find suitable models and methods for evaluating risk, which is a significant indicator used to calculate return volatility in financial markets in developed and emerging nations. This paper employed the daily data drawn from the weighted equity market indices of two emerging markets: the Shanghai Stock Exchange (SSE) and the Ghana Stock Exchange (GSE). The study period spans 14/10/2011 to 18/09/2020. This study employs empirical modeling methods. Following the heteroscedasticity model in most financial literature, the return and volatility relationship between SSE and GSE is investigated. The series' stationarity is tested by employing the Augmented Dickey-Fuller (ADF) unit root testing methodology.

Also, asymmetries in returns and volatility are conducted using the GARCH models. Again, Transfer Entropy, Granger Causality, and DCC GARCH were used to diagnose the two markets' information flow, causality, and volatility spillover. ARMA model was used to determine the best-fitted model for the two financial markets.

3.1 Granger Causality Test

The Granger Causality Test investigates the transmission effect of time series returns in Chinese and Ghanaian stock markets. The granger causality model was used to examine whether Shanghai Stock Exchange –

Composite Index (SSE-CI) has an impact on market returns of the Ghanaian Stock Exchange Composite Index (GSE-CI) or the GSE-CI returns have an effect on SSE-CI, or there is the existence of bidirectional causality on both GSE-CI and SSE-CI. This implies that events that occurred in the past may cause similar events to occur in the present. After determining the long-run relationship between the two stock market indices, the interaction of their variables must be investigated. If the probability value approaches the crucial significance of 5% when testing the null hypothesis, the null hypothesis is accepted, meaning no causality between the two indexes' variables. The following two equations illustrate the Granger Causality for the two markets to find if $\beta_i = 0$ for all lags i :

$$r_{t,1} = \sum_{i=1}^{\infty} a_i r_{t-i,1} + c_1 + v_1(t) \tag{2}$$

$$r_{t,1} = \sum_{i=1}^{\infty} a_i r_{t-i,1} + \sum_{i=1}^{\infty} \beta_i r_{t,2} + c_1 + v_2(t) \tag{3}$$

where r = returns, t = time,

3.2 Transfer Entropy

The quantity of guided (time-asymmetric) knowledge transfer between two randomized procedures is quantified by transfer entropy, a nonparametric statistic model. The proof of both markets' transmission is examined by Transfer Entropy. Transfer Entropy from one GSE process to another SSE is the amount of uncertainty in future SSE values that is minimized by knowing past GSE values given past SSE values.

The application of knowledge-based measures, such as Transfer Entropy, which was proposed by Thomas Schreiber and adopted by Hussain, Murthy & Singh (2019) as a calculation of the amount of information that a source sends to a destination, to further investigate the notion of which markets influence one another. Since the volumes of information transmitted from the source to the destination do not have to be the same as the amount of data transferred from the destination to the source, such a measure must be asymmetric. It must also be dynamic-as averse to mutual knowledge, which encodes information distributed between the markets of the two nations. Transfer Entropy based on Shannon Entropy measure is given by Shamshir, Mujahid, Baig & Mustafa (2019) as:

$$H = - \sum_{i=1}^N p_i \log_2 p_i \tag{4}$$

where the sum is generally the two countries indices for which $p \neq 0$. The base 2 for the logarithm is selected so that the information is given in the smallest amount possible. The average uncertainty about measurements i of a variable X is represented by Shannon Entropy, which evaluates the average number of series necessary to transform the variable X . Given a time series of a stock market index spanning over a specific range of values, one can divide the possible values into N different series and then calculate the probabilities of each state i . The statistical causality of Transfer entropy with a coupling method of (X, Y) where $P_y(y)$ is the cumulative distribution function of the random variable Y and $P_{X,Y}(X, Y)$ is the joint probability density function between X and Y . The joint entropy between X and Y is given by the equation 5:

$$H(H, Y) = - \sum_{X \in X} \sum_{Y \in Y} P_{X,Y}(X, Y), \log P_{X,Y}(X, Y) \tag{5}$$

The conditional entropy is defined by the underneath equation 6:

$$H(Y, X) = H(X, Y) - H(X) \tag{6}$$

It is, therefore, explained that $H(Y, X)$ is interpreted as the unpredictability of Y given the realization of X .

3.3 GARCH (Generalized Autoregressive Conditional Heteroscedasticity)

GARCH is a time series method of moment and autocorrelated conditional variance. Bollerslev suggested the GARCH model as an alternative method for obtaining long-lagged results with fewer parameters. It is a one-of-a-kind generalization of the ARCH model that is expressed as:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \dots + \beta_p h_{t-p} \tag{7}$$

The magnitude of the squared errors in the previous q periods determine the variance of individual periods. Since GARCH methods are autoregressive, the model estimates current variance using past squared observations and past variances. Because of their usefulness in estimating stock return and volatilities, GARCH approaches are usually used in finance.

The structure of ARMA and GARCH processes is strikingly similar: a GARCH p, q features a polynomial $\beta(L)$ of order " P " - the autoregressive term, and a polynomial $\alpha(L)$ of order " q " - the moving average period.

3.4 Dynamic Correlations

The Dynamic Conditional Correlation (DCC GARCH) is a conditional variance and correlation model (Poon et al. 2002). The general idea of the models in this class is that the covariance matrix, H_t , can be decomposed into conditional standard deviations, D_t , and a correlation matrix, R_t . In the DCC-GARCH model, both D_t and R_t are intended to be time-varying. Multivariate GARCH models linear in squares and the cross result of data are commonly used to quantify time-varying correlations. The DCC GARCH has the versatility of univariate GARCH models with sparse parametric models for correlations. They are not linear, but they can usually be calculated in simple terms using univariate or two-step likelihood function-based methods. It demonstrates that they can perform well in a variety of circumstances and provide reliable analytical results.

The DCC GARCH model for SSE and GSE returns assumed to be, a_t , with n assets and an estimated value of 0, as well as the covariance matrix H_t . The model for DCC GARCH is given as:

$$r_t = \mu_t + a_t \tag{8}$$

$$a_t = H_t^{1/2} z_t \tag{9}$$

$$H_t = D_t R_t D_t \tag{10}$$

r_t is the vector of log-returns of n assets at the time t .

a_t is the vector of mean-corrected returns of n assets at time t , i.e., $E[a_t] = 0$. $Cov[a_t] = H_t$.

μ_t is the vector of the expected value of the conditional r_t .

H_t $n \times n$ matrix of conditional variances of a_t at the time t .

D_t a $n \times n$ diagonal matrix of conditional standard deviations of a_t at time t .

R_t conditional correlation matrix of a_t at time t .

z_t vector of i.i.d errors such that $E[z_t] = 0$ and $E[z_t z_t^T] = 1$.

μ_t in equation (8) may be modeled as a constant vector or a time series model.

4.0 RESULTS AND DISCUSSION

4.1 Trend Comparison of GSE and SSE Composite Index 2011/10/14 - 2020/09/18

The Ghana stock market's return on the index for 2013 places it among the best-performing stock markets in Sub-Saharan Africa. The GSE – Composite Index (GSE-CI) recorded 78.81% in gains within 2013. The GSE Composite Index's year-end value amounted to €659 million in 2018 compared to a record of €56,791.28 million in 2019. Within the year 2020 to an early section of 2021, the exchange recorded fluctuating values in September (2020) 1856.92, December (2020) 1941.58, and February 5 (2021) 2054.96 with an upward trend of +3 (+0.13%) seeming progress amidst the COVID-19 however the impact is still felt (Trading-economics 2021).

The performance of all stocks listed on the Shanghai stock exchange is reflected in the SSE Composite index. In millions of Renminbi, the SSE Composite index had a year-end value of 2,493.9 in 2018 and 3050.12 in 2019. The difference, which is 556.22, signifies a favorable sign with a percentage gain of 22.30% in the year. Again, within the year 2020 to an early section of 2021, the exchange recorded fluctuating values, in September (2020) 3218.05, December (2020) 3473.07, and February 5 (2021) points of 3496.03, although records show increasing figures, however, its percentage on 2021 February 5 was -0.16%. An indication of the COVID-19's effect on its performance (Bloomberg 2021).

Figure 3 indicates the trend of the GSE and SSE from 2011 through 2020. The trend analysis based on Figure 3 demonstrates that the Shanghai Stock market was undoubtedly of excellent performance from 2011 to late 2017. The highest period of all best performance records was 2015, as can be observed from Figure 3. The GSE raised the standard of performance a little above SSE from late 2013 to the later part of 2014 and from the latter part of 2017 to the middle of 2018. Afterward, the Shanghai stock exchange took over its excellent performance until the end of the year 2019. In summary, SSE has had a higher record of performance than the Ghana stock exchange, but there were periods where GSE surpasses SSE concerning performance. This demonstrates that the two markets shared some similar characteristics.

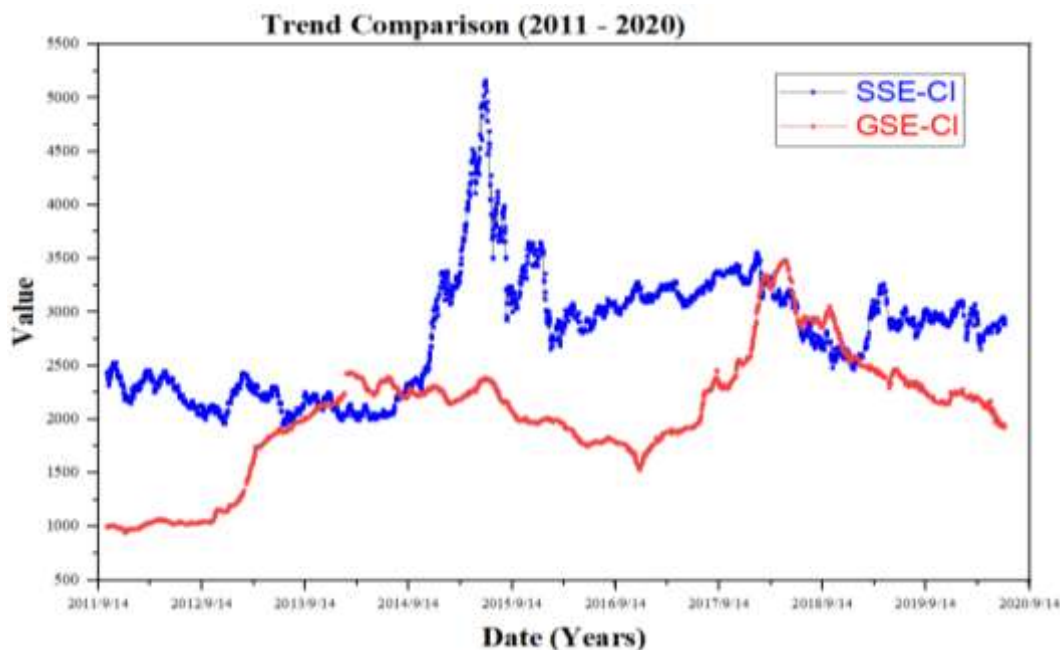


Figure 3 Composite index trend

4.2 Descriptive Statistics of the Ghanaian and Shanghai Stock exchange returns

Table 1 shows the statistical summary for daily observations of the Ghana Stock Exchange Index (GSEI) and the Shanghai Stock Exchange Index (SSEI) from 2011.10.14 to 2020.09.18, which includes mean, median, maximum, minimum, skewness, kurtosis, and Jarque-Bera test results for a total of 1992 observations.

Table 1. Summary of Descriptive Statistics of Composite Index Returns of GSEI and SSEI

	RGSE	RSSE
Mean	0.00033	9.52E-05
Median	5.99E-05	0.00056
Maximum	0.07847	0.06369
Minimum	-0.03829	-0.08906
Std. Dev.	0.00653	0.01428
Skewness	1.229351	-1.03009
Kurtosis	20.25765	10.09351
Jarque-Bera	25221.35	4528.668
P-value	0.00000	0.00000

The average daily observations of GSEI are (0.000333) while SSEI is (9.52E-05), indicating that there were gains in both markets over the study period; also, the standard deviations were GSEI 0.006532 and SSEI 0.014276. There is a substantial gap between the maximum of GSEI (0.078467) and minimum (-0.03829), while SSEI had a maximum of (0.063693) and minimum (-0.089058), which bolsters the high degree of return variability. In a normally distributed sequence, skewness must be 0, and kurtosis should be about 3. In the case of SSEI, it is negatively skewed (-1.030091), implying that the distribution has a long-left tail and a deviation from normality, while the GSEI is positively skewed (1.229351), indicating that the distribution has a heavy right tail. The GSEI and SSEI returns are both leptokurtic, meaning that the returns are fat-tailed, with large kurtosis figures of 20.25765 and 10.09351, respectively, exceeding the average value of 3.

Since the Jarque-Bera test for normality is acceptable at a 5% level, it is compatible with the results of both kurtosis statistics and skewness. This means rejecting the null hypothesis and accepting the alternative hypothesis that returns are not normally distributed. These outcomes agree with (Mlambo, Smit & Biekpe 2003)

conclusions that enshrine emerging market returns are not normally distributed. Hence, this study used the Student- *t* distribution when fitting the ARCH and GARCH family models.

4.3 Augmented Dickey-Fuller (ADF) test

The ADF test was performed to investigate whether the two countries' daily composite index returns are stationary. As a result, both GSE and SSE's lag-length has been automatically selected based on the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC), with a maximum lag length of 25. Table 2 summarizes the findings.

Table 2 SSE and GSE Augmented Dickey-Fuller test at the level and log

ADF RESULTS	1% level	5% level	10% level	T-Statistics	P-value
SSE_CI	-3.4334	-2.8628	-2.5675	-2.0187	0.2789
RSSE	-3.4334	-2.8628	-2.5675	-43.1627	0.0000
GSE_CI	-3.4335	-2.8628	-2.5675	-1.9278	0.3196
RGSE	-3.4335	-2.8628	-2.5675	-9.2413	0.0000

From Table 2, it can be concluded that no variables were stationary at the log level as the P-values or the critical values are more significant than the test statistics at the 5% level. As a result, at the log level, the null hypothesis was accepted. It is crucial to make these variables stationary. At first log difference, all the variables' null hypothesis was rejected and accepted the variables' alternate hypothesis. The variables had a test statistic, which was more negative than the critical values. All of the variables in the sample were, on average, stationary at order one (1).

4.4 Return and Volatility Model Specification for lags of ARMA models

This study used several parameters of Autoregressive Moving Average (ARMA) (p, q) models to determine the best-fitted model for the composite index return. Table 3 displays the effects of the proposed ARMA models and their Akaike's Information Criteria (AIC) and Schwartz's Information Criteria (SIC) values.

Table 3 ARMA Order of (p, q) GSE and SSE

ARMA (p, q)	GSE AIC	GSE SIC	SSE AIC	SSE SIC
ARMA (1,1)	-7.28366	-7.27242	-5.66805	-5.65681
ARMA (1,2)	-7.24214	-7.23090	-5.65978	-5.64854
ARMA (1,3)	-7.22749	-7.21626	-5.66312	-5.65188
ARMA (1,4)	-7.25293	-7.24169	-5.65817	-5.64693
ARMA (2,1)	-7.24884	-7.23760	-5.65980	-5.64857
ARMA (2,2)	-7.28304	-7.27180	-5.66049	-5.64926
ARMA (2,3)	-7.25262	-7.24138	-5.66335	-5.65211
ARMA (2,4)	-7.27051	-7.25927	-5.65852	-5.64728
ARMA (3,1)	-7.22857	-7.21733	-5.66285	-5.65161
ARMA (3,2)	-7.24699	-7.23575	-5.66300	-5.65177
ARMA (3,3)	-7.25528	-7.24404	-5.66529	-5.65405
ARMA (3,4)	-7.25723	-7.24599	-5.66155	-5.65031
ARMA (4,1)	-7.25811	-7.24687	-5.65827	-5.64703
ARMA (4,2)	-7.27420	-7.26296	-5.65853	-5.64729
ARMA (4,3)	-7.26148	-7.25024	-5.66189	-5.65066
ARMA (4,4)	-7.26513	-7.25389	-5.65752	-5.64628

A careful observation of table 3 depicts that ARMA (1,1 through 4,4), when keenly observed, it could be realized that the ARMA (1,1) model has the least value of AIC and SIC for both markets SSE and GSE, respectively. The AIC and SIC for GSE ARMA (1,1) are (-7.28366) and (-7.27242), and the corresponding AIC and SIC for SSE ARMA (1,1) are (-5.66805) and (-5.65681), respectively. The results indicated that the two

financial markets' best-fitting model is ARMA (1,1) because of the lowest AIC and SIC values obtained. This model assumes that the composite index return data series is subject to autoregressive order one and a moving average of order 1. In summary, this exciting result contradicts the many findings which stipulate that emerging countries' stock markets data suits a particular model.

4.5 Using Dynamic Conditional Correlation GARCH to test for SSE and GSE index data.

The results obtained for estimating the ARMA (1,3) (1) DCC GARCH model for SSE and GSE are shown in table 4.

The estimation of the residuals of DCC GARCH ARMA (1,3) (1) of the SSE and GSE shows a mean equation with a significant coefficient for SSE (0.000207) and GSE (2.77E-06), respectively. The p-values of SSE and GSE are 0.3734 and 0.9937. Since the p-values are more significant than 5%, it portrays that the sequence is not statistically significant. However, SSE and GSE's variance equation illustrated a statistically significant coefficient of (1.25E-06) and (5.84E-06) accordingly. The actual results obtained indicated that there is a transmission of information in both markets. The ARCH residuals and the GARCH values are positive. Again, observation of their AIC's and SIC's values indicated that GSE, compared to SSE, has the lowest AIC of (-7.422981) and SIC (-7.403289). The afore analysis justifies the desirability of the residuals of the DCC GARCH ARMA (1,3) (1) model.

Table 4 The residuals of DCC GARCH ARMA ((1,3), (1)) model for RSSE and RGSE

	DCC GARCH ARMA (1,3) (1) (SSE)	DCC GARCH ARMA (1,3) (1) (GSE)
Variable	Coefficient	Coefficient
C	0.000207**	2.77E-06***
AR (1)	-0.973991	0.869588
AR (3)	0.005058	0.050719
MA (1)	0.995492	-0.801807
VARIANCE EQUATION		
C	1.25E-06***	5.84E-06***
Residual (-1) ^2	0.073756**	0.126056*
GARCH (-1)	0.922874***	0.731074*
P-values	0.3734	0.9937
AIC	-6.029261	-7.422981
SIC	-6.009569	-7.403289

For the SSE and GSE, Table 5 shows the combined estimate result of the DCC GARCH (1, 1) model with Univariate GARCH fitted in the first step.

Table 5 DCC GARCH (1, 1) model with Univariate GARCH fitted in the first step.

	DCC GARCH (1,1) for SSE and GSE	
Variable	Coefficient	P-Values
theta (1)	-0.004400**	4.83E-09***
theta (2)	-0.0976164**	0.0000***
C (9)	0.043871**	0.0825**
AIC	-13.4589	
SIC	-13.4465	

The DCC-GARCH (1,1) model of the two financial markets yielded significant results; in other words, the two groups of residuals have obvious heteroscedasticity. The theta (1) and theta (2) coefficients -0.004400 and -

0.976164 for SSE and GSE are also significant. Again, the p-values for SSE 4.83E-09 and GSE 0.0000 are significant. The DCC GARCH results also portray that stability conditions were met: $\theta(1) + \theta(2)$ is less than 1. They are implying that the variance connection between the two markets will not be affected by short-term fluctuations. The DCC coefficient is 1% significant; that is, the dynamic variance connection is significantly affected by its own earlier stage; that is, the long-term volatility relationship substantially impacts the two markets.

RHO_12_

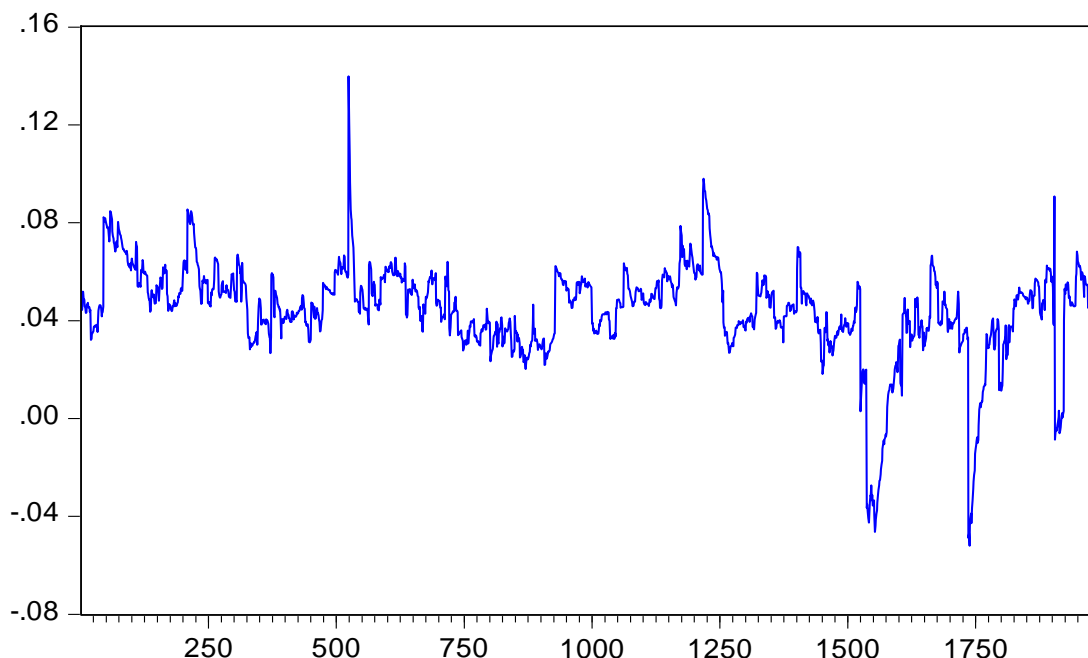


Figure 4 DCC Correlation Coefficients

The dynamic correlation coefficient graph for the two financial markets is shown in Figure 4. It can be seen that the overall correlation degree is maintained at a very low level. And it is worth noting that the overall correlation coefficient is a positive correlation. As a result, it is clear that the correlation increases at specific points in time (thus, it can be analysed with specific events). It implies that the connection between these two markets moves in tandem. Finally, it could be observed from the graph that there are days where the market experienced an enormous fluctuation due to the COVID19 Pandemic having severe repercussions on the two stock markets as observed from the graph within 1500 - 1992 days, which indicate that the correlation coefficient tends to vary from previous results, which can be compared to the period's trend.

4.6 Granger Causality for GSE and SSE

The Granger Causality test for the two markets with the null hypothesis: R_GSE does not Granger-cause R_SSE exhibits beneath results as portrayed in table 6:

Table 6 Test Results of Granger Causality

lag	1	2	3	4	5	6
R_GSE to R_SSE	1.160	0.608	0.541	0.402	0.494	1.169
R_SSE to R_GSE	0.356	0.823	0.699	0.833	0.654	0.584

Note: The numbers in the table are F-statistics with their respective lags (1-6) for R_GSE to R_SSE and R_SSE to R_GSE

The results ascertained from the Granger Causality indicate that there are no significant values for F-statistics, which means no causality in Granger between R_GSE and R_SSE and vice versa. The P-values obtained were more significant than 5% for the critical values. The above null hypothesis must be accepted; R_SSE does not granger cause R_GSE, and R_GSE does not granger cause R_SSE. This implies no causal relationship between the GSE-CI and R_SSE, which indicates a bi-directional non-causation. The effect is that

R_SSE cannot be used to predict the future values of the R_GSE, and also, R_GSE is not vital in measuring the Composite Index of R_SSE. Thus, SSE_CI does not influence the pattern of the GSE_CI and vice versa.

4.7 The Transfer Entropy

Transfer Entropy is a nonparametric statistic measuring the quantity of directed information transfer between two random processes, each of which is represented by $TE_{SSE \rightarrow GSE}$. $TE_{SSE \rightarrow GSE}$ which enshrines that information flow from the SSE could have an impact on information flow from the GSE. Transfer Entropy captures any dependency connections between two-time series.

Table 7 Transfer entropy Test

lag	1	2	3	4	5	6
R_SSE to R_GSE	0.0051	0.0271**	0.0469	0.0811	0.1079*	0.1184
R_GSE to R_SSE	0.0054	0.0239	0.0564**	0.0947***	0.1170**	0.1241

Note: *, **, *** indicate significance at 1%, 5%, and 10% respectively.

The daily series of the two markets portray evidence of significant transmission based on the results obtained. This gives enough justification for the transmission of information between the two markets when their lagged values are compared. Although there are variations in values concerning the selected lags with the time-series data, the variations indicate transmission significance. The two markets' daily series portrays that Transfer Entropy captures non-linear causality between the two Stock markets, particularly in terms of their movements. Their connection suggested that the series does change for years of crisis however remains relatively intact within a short period of impact, as observed in the composite index trend analysis of Figure 3.

The results finally show that based on transfer entropy, the Shanghai stock exchange has a significant causal impact on the Ghanaian stock exchange with the second-order lag. Simultaneously, there is a significant causality from the Ghanaian stock exchange to the Shanghai stock exchange with the third through fifth orders of lags. This implies the asynchronous return transmission between Shanghai and Ghanaian stock markets. In summary, by comparing Granger Causality to Transfer Entropy, the Transfer Entropy indicated significant transmission while Granger Causality indicated no causality because all the Granger Causality values were not significant for both series.

5.0 DISCUSSION

Specifically, this study employed the ARMA, GARCH, Granger Causality, Transfer Entropy, and DCC GARCH model to analyse the Ghanaian and Shanghai stock composite index to ascertain their current performance and volatility pattern before and during the COVID-19 Pandemic. Initially, the ARMA model was estimated to determine the best-fitted model for each composite index. It was concluded that ARMA (1,1) model fits better for the two markets. This result adds new knowledge to the existing literature; formerly, most researchers conclude that model selection for emerging markets suits each country's gathered data. The transmission of both markets' returns was examined by the Granger causality test and transfer entropy.

In contrast, the dynamic correlation between the market is examined by adopting the DCC-GARCH model. The findings indicated that the Chinese stock market has a significant causal effect on the Ghanaian stock market with a second-order lag. In contrast, the Ghanaian stock market has a significant causal impact on the Chinese stock market with the third through fifth lags. This implies the asynchronous return transmission between Chinese and Ghanaian stock markets. Furthermore, it was realized that long-term volatility would significantly impact the two markets. However, the short-term fluctuations would not heavily affect the stock exchanges based on the DCC-GARCH model. The residuals of the DCC GARCH for GSE and SSE had an insignificant probability value, which indicates that long and persistent volatility may negatively impact the stock markets.

The DCC graph also demonstrates that the overall correlation degree is maintained at a very low level. And it is worth noting that the overall correlation coefficient is a positive correlation. Hence, it is worth emphasizing that the correlation increases obviously at specific periods. This implies that the connection between these two markets moves in tandem. It was observed from the DCC graph that there are days where the market experienced an enormous decline due to the COVID19 Pandemic having severe repercussions on the performance of the two stock markets. The Granger Causality results indicated insignificant values for the distribution, which means no causality in Granger between R_GSE and R_SSE and vice versa. Further, both markets showed heteroscedasticity, fat tails, and peakedness.

Finally, the researchers discovered that many emerging market studies are interested in adopting and comparing various ARCH/GARCH family models and ARMA models using data from emerging countries. Typically, each empirical analysis uncovers the best-fitting models in their respective stock markets such as; (Humavindu & Floros 2006), and (Emenike 2014) in Nigeria, (Su 2010) in China, (Angabini & Wasiuzzaman 2011) in Malaysia, (Kenawy 2013) in Egypt, (Neaime 2012) in Saudi Arabia and (Chkili & Nguyen 2014) in

Jordan. All of them used one or more of the following models: ARMA, ARCH, GARCH, Transfer Entropy, and DCC GARCH. The core principle derived from these previous studies demonstrated that GARCH and ARMA are the best models for measuring volatility, detecting clustering effect, leptokurtosis, and the leverage effect, consistent with the findings of this study. This research also came up with new findings based on the ARMA model's results, indicating that emerging markets data could be examined to obtain one fitted model for two countries.

6.0 CONCLUSION

This study used the Daily Composite Index data gathered from the Shanghai Stock Market and the Ghanaian Stock Market from 2011/10/14 to 2020/09/18. The study employed empirical modelling methods to aid these models ARMA, GARCH, Transfer Entropy, Granger Causality, and DCC GARCH. Throughout the study, these models were used to estimate the returns and volatility patterns of the stock markets composite index, enhance the accuracy of the investigation, and have a systematic and in-depth analysis. The main conclusions of this study are as follows:

Firstly, the trend comparison analysis conducted on the SSE and the GSE demonstrates that the two markets shared some similar characteristics apart from market size, year of operation, continent, and capitalization. The study results emphasized that stock market returns are ascertained based on effective and efficient operations but not guaranteed by size, capitalization, and the number of years. Hence, supporting the hypothesis that the two markets connect concerning their stock return composite index and volatility patterns.

Secondly, it was realized that the two markets have operated on stable ground for over 25 years and have attracted several industry giants across the globe, and are characterized by a high growth rate, stable performance, and solid profitability.

Finally, the study established that high volatilities are characterized in Ghanaian and Shanghai markets in periods of financial contagion and pandemics such as the recent COVID19 that have had an enormous repercussion on the two stock markets. Again, the Ghanaian Stock exchange occasionally experiences higher fluctuations in the years of elections either before or during but become stable right after the elections due to investors' behaviour. This emphasized the risk-averse nature of many investors in such periods.

This study recommends that policymakers and investors adopt diversification as a resort to financial management, as enshrined in the current modern portfolio theories that state that "it is prudent not to put all your eggs in one basket." This study concluded that the stock market provides capital for development and any nation that seeks economic growth must aim at developing its stock market.

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