

Investigating the impact of COVID-19 pandemic on volatility patterns and its global implication for textile industry: An empirical case study for Shanghai Stock Exchange of China

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ABSTRACT – REZUMAT

Investigating the impact of COVID-19 pandemic on volatility patterns and its global implication for textile industry: An empirical case study for Shanghai Stock Exchange of China

This research paper aims to examine the impact of the COVID-19 pandemic on volatility patterns and its global implication for the textile industry in China. The COVID-19 pandemic has generated a global health crisis with profound economic, social and financial implications, but also has triggered a ruthless global recession. The global economic recovery as a result of the COVID-19 pandemic can also generate significant investment opportunities for the textile industry in China. In this paper, the application of empirical methods could explain historical prices, the movement dynamics of financial assets, and investigate various important characteristics of asset pricing that explore details of the Chinese stock market. The econometric framework includes the following: symmetric Generalized Autoregressive Conditional Heteroscedastic GARCH (1, 1) model, asymmetric GARCH models such as EGARCH and GJR models. The main aim is to identify the asymmetric volatility effect, and impact of news on the SSE Composite Index and investigate long memory properties in volatility using daily data for the sample period from 19th December 1990 to 31st December 2020. This empirical study contributes to the existing literature on the impact of the COVID-19 pandemic on international stock markets, by investigating symmetric and asymmetric volatility patterns in the case of the Shanghai Stock Exchange from China.

Keywords: GARCH family models, symmetric volatility, asymmetric volatility, COVID-19 pandemic, apparel, textile industry, economic recession, leverage effect

Analiza impactului pandemiei COVID-19 asupra modelelor de volatilitate și a implicațiilor sale globale pentru industria textilă: Un studiu de caz empiric pentru Shanghai Stock Exchange din China

Acest articol de cercetare își propune să examineze impactul pandemiei COVID-19 asupra modelelor de volatilitate și implicația sa globală pentru industria textilă din China. Pandemia COVID-19 a generat o criză globală de sănătate cu implicații economice, sociale și financiare profunde, dar a declanșat și o recesiune globală semnificativă. Redresarea economică globală ca urmare a pandemiei de COVID-19 poate genera, de asemenea, oportunități de investiții semnificative pentru industria textilă din China. În acest studiu de cercetare, aplicarea metodelor empirice ar putea să explice prețurile istorice, dinamica comportamentală a activelor financiare tranzactionate și să investigheze diferite caracteristici importante ale prețului activelor care explorează particularitățile pieței bursiere din China. Abordarea econometrică include următoarele: modelul simetric GARCH (1, 1), modelele GARCH asimetrice precum modelele EGARCH și GJR. Scopul principal este de a identifica efectul de volatilitate asimetrică și impactul știrilor asupra indicelui compozit SSE, precum și de a investiga proprietățile memoriei pe termen lung în volatilitate folosind date zilnice pentru perioada de eșantionare din 19 decembrie 1990 până la data de 31 decembrie 2020. Acest studiu empiric are contribuție în literatura de specialitate existentă privind impactul pandemiei COVID-19 pe piețele bursiere internaționale, prin investigarea modelelor de volatilitate simetrice și asimetrice în cazul Shanghai Stock Exchange din China.

Cuvinte cheie: modele GARCH, volatilitate simetrică, volatilitate asimetrică, pandemie COVID-19, îmbrăcăminte, industria textilă, recesiune economică, efect de levier

INTRODUCTION

COVID-19 pandemic has generated impressive losses but also attractive advantages for the global economy. The interaction between the financial market and the real economy can lead to sustainable economic growth, including based on the efficiency of the textile sector of China. World Bank indicates that the U.S. has been in the first position with financial market

capitalization followed by an Asian emerging economy, China, in the second position. Historical statistics suggest that China was not even in the top five countries with high market capitalization till 2004. In the journey of the next 12 years, i.e., 2016, the Asian giant has secured the second position with financial market capitalization. Shanghai Stock Exchange has now had a market capitalization of over 6 trillion

starting with a base index point of 100 in December 1990, which grew up to over 6000. There are several interesting market movement pattern that makes SSE China different from any other financial market. For instance, in the period 2004–2006, the time before the global financial crisis, when most of the world's financial markets are making new historical highs, the Chinese market (SSE) made its low, 1013 rim billion. Surprisingly, in the year 2007 and emerging weeks of 2008, when most of the financial markets were weak, and struggling to sustain the market, the SSE made its lifetime high trading levels global financial crisis was about to hit the world's financial markets. It is the exact time just before the global financial crisis impacted the reported high to 5903 rim billion.

Very recent, the effect of COVID-19 where most of the financial market performing weaker during December and January 2020, there was not any strong impact on SSE initially until more cases were reported, the major impact started from February 2020. Only a few major corrections appear in the movement pattern of SSE, which has wiped off billions of investors' investments, created panic out of investor's predictions and that panic escalated to the rest of the world's financial markets. The first case was identified on 4th January 2020, no changes were abstracted by SSE, and even a few more cases were reported up to 20th January 2020, still no change in SSE movement pattern until 23rd January, COVID-19 impact started with the first loss of over 200 rim billion. At the same time, the rest of the financial markets also abstracted on an average of more than 8% corrections due to novel pandemics. Volatility in the financial market changes the value of the investment. Castañeda-Navarrete et al. [1] suggested that the COVID-19 pandemic significantly affected international trade and global value chains, including the global apparel industry. The COVID-19 pandemic generated considerable losses in the global production system. Frederick and Daly [2] have conducted a grounded statistical research study and concluded that is still one of the most important apparel producers and exporters in the world. Moreover, the apparel industry in China has experienced favourable and competitive dynamics in recent decades because it has a great diversity of products and materials. Song et al. [3] investigated the effect of the COVID-19 pandemic on the manufacturing field in China and proposed an opportune alternative solution to creating a regional value chain in manufacturing managed by China, Japan and South Korea.

Volatility is one of the strongest fundamental parameters that create changes in asset prices. When asset price falls from the purchase price, it increases risk and stock returns. Volatility is the result of a combination of negative and positive shocks at the same time with different volumes of trades. Black [4] introduced the innovative concept that has explored details of the financial market and asset price – the

concept of the leverage effect. The phenomenon introduced as the leverage effect indicates that negative shocks in previous volatility impact more negative shocks compared to positive shocks. This concept has captured worldwide attention. The financial market looked symmetric correlations until the introduction of the leverage effect. This asymmetric concept extended visibility and forecasting to asset price movement. The symmetric approach of volatility modelling focuses on volatility clustering that reflects in always positive autocorrelation of squared returns appearing movements to deterioration to zero.

This paper explores the Chinese Stock Market considering the Shanghai Stock Exchange index from the beginning of time i.e., 19th December 1990 to 31st December 2020 considering daily closing prices for 30 years. The paper focus to innovate 1) volatility estimation, 2) the presence of leverage effect, 3) impact of news and reaction of Chinese stock exchange index, and 4) index movement pattern and risk-return prospects. In December 2019, a novel coronavirus was identified that later spread in Wuhan, China. Inter-transmitted volatility details of the Shanghai Stock Exchange Composite Index were used to identify the probability distribution of asset price dynamics. Volatility change highlights important evidence in asset returns. Despite such invention, no impact appears anywhere during January 2020, until it was declared pandemic and uncertain fall started to appear from February 2020. We cover the impact of high volatility shocks during COVID-19 panic time which has created uncertain movements in the Shanghai Stock Exchange. A natural way to interpret financial series volatility estimation is to examine statistical relevance between investment and output at time t . Volatility is indicated by ups and down in index prices so as in asset prices. The most influential innovation by Robert Engle [5] represents the ARCH model that estimates volatility, further generalized by Bollerslev [6] that captures volatility clustering of asset prices so the model is symmetric along with one ARCH and one GARCH effect. Moreover, Birau et al. [7] conducted a research study and the empirical results suggested that GARCH (1, 1) model is not fitted for the sample stock markets of Spain and Hong Kong in the context of the COVID-19 pandemic. Brooks and Rew [8] argued that the GARCH model is the most representative and accurate for modelling volatility in financial time series data. We employ GARCH family models to estimate the volatility of the most representative stock index of SSE from China, which is the Shanghai Stock Exchange (SSE) Composite Index.

This research paper is structured as follows: the subsequent section presents a literature review. The third section covers the methodology used in the econometric approach to GARCH and GARCH Family models. The following section covers empirical analysis, presentation of the statistical property and detailed interpretation of the SSE Composite

index movement. Conclusion marks and findings are presented in the fifth section.

LITERATURE REVIEW

There are two significant schools of thought on volatility. One school of thought (Lockwood and Linn, 1990) argues that the introduction of futures trading increases the volatility in the spot market and thereby the market gets destabilized. Another school of thought [9] argues that the introduction of futures actually reduces the volatility and thereby the market gets stabilized, while GARCH analysis confirmed no structural change after the introduction of futures trading on the National Stock Exchange (NSE) of India. Further, Kumar [10] opines that derivative trading helps in price discovery, improves the overall market depth, enhances market efficiency, augments market liquidity, reduces asymmetric information and hence the degree of volatility of the cash market decreases. Thenmozhi [11] says that the movements in future prices provide predictable information for the movements of the index. She also agrees that the volatility gets decreased due to the introduction of futures. Shenbagaraman [12] has studied the impact of the introduction of derivatives on the spot market volatility. The study explained that the increased volatility of the Indian stock market was due to the increase in the volatility of the US market. Nath [13] has found in his study that volatility decreases due to the introduction of derivatives. Vipul [14] examined the change in volatility in the Indian stock market especially after the introduction of derivatives. It was identified that there was a reduction in underlying shares after the introduction of derivatives.

World Health Organization (WHO) defines COVID-19 as an infectious disease determined by a new type of coronavirus named SARS-CoV-2. Moreover, WHO was first informed about this extremely contagious virus included in the family of coronaviruses, on 31 December 2019, due to an explosion of cases of “viral pneumonia” identified in Wuhan, which is the capital of Hubei province in central China. Moreover, China was the first country in the world which implemented the restrictive measure of lockdown to limit the spread of COVID-19 infection cases. On the other hand, Batool et al. [15] argued that it is well-known fact that pandemics determine economic distress so it is no surprise that the COVID-19 pandemic is similar. Government authorities in countries all around the world have been forced to impose harsh measures and lockdown restrictions to limit the spread and high infection rate of COVID-19 despite the tremendous economic cost associated with them. The global economy has been severely affected by the COVID-19 pandemic since its outbreak in China. Zulfiqar et al. [16] suggested that the governance quality should be strengthened that set the direction of change to achieve greater financial stability and growth. However, Spulbar et al. [17] suggested that sustainable development represents a great challenge for the global economy.

According to World Trade Organization also known as WTO [18], the COVID-19 pandemic which generated a global health crisis with profound economic, social and financial implications is “an unprecedented disruption to the global economy and world trade, as production and consumption are scaled back across the globe”. Nicola et al. (2020) investigated the socio-economic impact of the COVID-19 pandemic and suggested that due to necessary measures such as social distancing, self-isolation and travel restrictions, it is expected to degenerate into severe economic crisis and recession.

The Organization for Economic Cooperation and Development also known as OECD investigated in March 2021 the impact of the COVID-19 pandemic on global financial markets and has identified significant shocks and turbulences compared to the turmoil and market risk aversion caused by the global financial crisis of 2007–2008 [19]. As an immediate consequence, stock markets have collapsed by more than 30% considering international stock market contagion, while the economic growth in China suddenly declined and the domino effect spread globally. Despite financial reforms, the severe economic recession has affected most countries all around the world.

Bahrini and Filfilan [20] examined the effect of the COVID-19 pandemic on stock returns in the case of Gulf Cooperation Council (GCC) countries for the sample period from April 1, 2020, to June 26, 2020. The empirical findings indicate that daily returns of the major stock market indices, in the GCC member states, such as ADSMI for Abu Dhabi of the United Arab Emirates, BHSEASI for Bahrain, MSM30 for Oman, SASEIDX for Saudi Arabia and DSM for Qatar, decreased as the number of confirmed deaths increased. Zhang et al. [21] have conducted an empirical study based on unsophisticated statistical analysis to determine the global implications of the COVID-19 pandemic, which is a global health crisis, on stock market risk in the case of financial markets all over the world. This empirical study included stock market databases collected for the top 10 most infected countries based on several confirmed cases of COVID-19 infection, together with Japan, South Korea and Singapore, while Iran is excluded due to unavailable data, up to March 27, 2020. The empirical findings revealed that the reaction of global financial market risks was characterized by a consistent increase due to the COVID-19 outbreak. Moreover, the impact of the COVID-19 pandemic generated high uncertainty and economic losses which determined that stock markets have become highly volatile and unpredictable.

Thus, there are two types of observations; one is that volatility increases if futures and options are introduced and the other is that the degree of volatility decreases or the stock market gets stabilized for the introduction of the futures segment. Dulababu [22] in his study reveals that the India VIX is not taken as a source of an opportunity to make returns. Further, the Indian traders treat the India VIX as a fear index.

They perceive it as a threat and a danger signal and hence they avoid trading when the market is falling. Unless the stock market becomes more and more sensitive to multiple external factors such as Govt policies in the country, wide and in-depth population exposure to the stock market after intensive awareness programs to encourage the public to have exposure in the equity market, global stock markets' movements, developed and dominating country economic policies etc, the India VIX and other instruments as mentioned above may not become a popular instrument to trade and invest in.

Chaudhary et al. [23] examined stock market volatility in the case of the most representative 10 countries in the world, using GDP databases, i.e.: the United States (S&P 500 index), China (Shanghai Composite index), Japan (Nikkei index), Germany (Dax index), India (BSE-Sensex index), the United Kingdom (FTSE100 index), France (CAC40 index), Italy (FTSE Italia All Share index), Brazil (IBX40 index) and Canada (S&P TSX Composite index). The econometric framework included the following: Descriptive Statistics, Unit Root Test, ARCH effect test and (GARCH) (1,1) model for the sample from the period from 1 January 2019 to 30 June 2020. The empirical findings revealed that GARCH (1,1) model exhibits the fact that the COVID-19 coefficient in the conditional variance equation has a substantial positive influence on conditional variance for all selected stock market indices, which indicates that the coronavirus pandemic has increased the volatility in the case of all these sample stock markets.

The volatility of the Shanghai stock index is found asymmetric by many researchers. To be specific, the negative information would engender more volatility than that caused by positive information. Numerous researchers like Sun and Yan [24], Gan [25] explored that the daily returns exist in the leverage effect of the two markets which indicates that the volatility caused by bad information shock is greater than that produced by the positive information with the same degree. This phenomenon resembles the feature of the mature stock market. Although the leverage effect confirmed the existence in the Shanghai and Shenzhen stock market, the results also show that the leverage effect in Shanghai Composite Index is stronger than Shenzhen Component Index. Similar findings were reported from other studies. Whereas, the results from research conducted by Liu and Zhang [26] and Huang [27] produced a very diverse set of events. Huang [27] suggested in his study came up that there is no significant leverage effect in the Shenzhen stock market. This researcher also pointed out that having no short-selling mechanism in the Chinese stock market might be the main reason. Although investors anticipate the stock price would fall further when the stock market is shocked by the negative information, only the investors who hold the shares would react to this. Though, the rest of the investors are not able to respond by selling stock so there is no remarkable leverage effect in a mature stock market. On the other hand, Liu and Zhang [26]

explored that the Shenzhen stock market has a more significant leverage effect and volatility than the Shanghai stock market.

Fan et al. [28] investigated the volatility dynamics of Chinese stock markets, such as the Shanghai and Shenzhen stock markets from January 2005 to June 2015 based on GARCH family models. The empirical findings revealed that EGARCH (1,1) model is the most suitable and fits the sample databases in both cases, while also providing a higher prediction accuracy than the other selected GARCH models. In other words, the EGARCH model fits both Shanghai and Shenzhen exchanges well with consideration of the following two aspects. One is the model selection criteria AIC and SC, and the other is the forecast performance based on the forecast evaluation statistics. Moreover, the Shanghai stock market exhibits a much higher leverage effect compared with the Shenzhen stock market. However, some other researchers just take one aspect into analysing. For instance, Pei and Xu [30] just compare the fitting results by some criteria such as R square, AIC and SC and then make the conclusion, which is similar to Huang [27]. Though, being only in the view of the model selection criteria is not enough to choose the best-fitted model. It is essential to evaluate the forecast performance of each candidate model as a reliable reference by comparing the forecast evaluation statistics such as MAE, RMSE and MAPE. Also, it's noteworthy that the fundamentals of these two classification methods are different which might lead to distinct results. Alexander and Lazar [30] also comment that the one with the most accurate forecast performance is the most appropriate model to fit the stock market among the competing models. In other words, the latter aspect is more essential than the former one to some extent.

The research of Fan et al. [28] examined the volatility behaviour of Chinese stock markets by some variations of the heteroscedastic (or heteroskedastic) conditional volatility models. The results show that the EGARCH (1,1) outperform other traditional models in modelling and forecasting the volatility of the Chinese stock market. AIC, SC, RMSE, MAE and MAPE model selection criteria give proof of the above judgement. In detail, when the daily returns are shocked and then perform the abnormal volatility, the impacts would not eliminate in the short term. Hence, the overall risk of the Chinese stock market is high to some extent. More importantly, there exist significant leverage effects in the daily returns series of both indices. That is, the volatility in the diminishing market tends to be higher than in the booming market. It indicates that the investment consciousness of most Chinese investors is relatively weak so investment behaviour is easily affected by all kinds of information. This is also noteworthy that the leverage effect in Shanghai Composite Index is greater than that in the Shenzhen Component Index which indicates that the speculation in Shanghai stock market is greater than in the Shenzhen stock market. Provided that the investors could recognize these

features of the volatility in the Chinese stock market, this may help them to avoid risk instead of noise trading, as well as provide a policy basis for decision-making departments of government to supervise the securities exchanges.

Moradi et al. [31] have conducted an empirical study on the effects of macroeconomic variables on stock price crash risk in the case of the Iranian market. The research results can be a red flag for political decision-makers in emerging markets struggling with financial issues to focus on the stock market in macroeconomic planning to avoid triggering a crisis and implicitly capital flight. The implementation of transaction policy has played an important role in the Chinese stock market in recent years. The phenomenon of sudden slump or rise in the prices of stocks has been brought down to a certain extent. Furthermore, the risk conduction mechanism is gradually developed. But there still exist many problems in the Chinese stock market. For instance, the stock market organization structure of Shanghai and Shenzhen could not effectively manage and deal with the occasional events, which caused strong impacts on the stock markets [32]. Regulators should take more stringent measures to reduce the number of vicious speculation and control the volatility. Understanding volatility in emerging capital markets is essential for determining the cost of capital and evaluating direct investment and asset allocation decisions. It would be of benefit for investors to identify risks and increase the awareness of risk investment.

DATA AND RESEARCH METHODOLOGY

From the above-reviewed literature, it is clear that researchers have explored various aspects of volatility in the stock market. The present study is an attempt to strengthen the existing literature. This paper focused to understand, analyse and explore volatility pattern and volatility clusters from the base index. Shanghai Stock Exchange (SSE) was introduced with a base index of 100 (99.98) on 19th December 1990 and a daily closing price considered for three decades. The daily closing price of the Shanghai Stock Exchange (SSE) Composite Index has been considered from 19th December 1990 to 31st December 2020 considering 7494 daily observations. The daily closing price of SSE is objected to provide historical evidence of the presence of volatility in today's price whether following the impact of yesterday's price, understanding price movement pattern, exploration of risk-return and impulse change in financial series movements.

The empirical study of the paper will provide support to understanding impulse magnitude, escalating risk-return and exploring the Shanghai Stock Exchange movement pattern. To meet with objected outcomes, we employ the application of several statistical tools that measure normality, movement of series pattern, explore volatility and leverage effect.

Statistical application set includes conversion to log, symmetric Generalize Autoregressive Conditional Heteroscedastic GARCH (1,1) model to estimate volatility, asymmetric GARCH model sets EGARCH and GJR to map leverage effect and predict the impact of the news. The financial series of SSE – China converted to log returns expressed in equation 1. During the process of the equation, r_t represents logarithmic daily returns of SSE China for time t , P_t indicates the closing price at time t , and similarly, P_{t-1} indicates the corresponding price of time $t-1$. Unit root test is applied to SSE China series return that determines stationary in the case of selected observations. Application of ADF property indicates that if ADF statistics is less than its critical value along with p-value > 0.05 , the null hypothesis is rejected, and the series return is ready for model application. This test employed to eliminate the normality of the distribution hypothesis, asymmetry distribution and kurtosis parameter (leptokurtic distribution) shown in equation 3.

Log conversion:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) = \ln(p_t) - \ln(p_{t-1}) \quad (1)$$

Symmetric GARCH (1, 1) model:

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \quad (2)$$

The variance equation assumption process assures that value of the constant is higher than 0. GARCH (1,1) represents the symmetric model that is extensively used to estimate volatility in time-series returns. One limitation of the symmetric model is that it does not capture the leverage effect which is required to have additional lags and exponential process, thus asymmetric GARCH type models i.e., EGARCH also called Exponential GARCH and GJR. Negative news creates a more pronounced effect on the financial market and probable impact measurement can be interesting in a manner to get an idea about the elasticity of market movement during a negative news reaction.

EGARCH by Nelson [33] captures asymmetric responses of time-vary variances to volatility shocks and also ensures that variance is always positive.

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^p \beta_j \log(\sigma_{t-j}^2) + \sum_{j=1}^q \alpha_j \left\langle \frac{s_{i-t}}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| - y_i \frac{s_{i-t}}{\sigma_{i-t}} \right\rangle \quad (3)$$

Another asymmetric model GJR is a variant of Threshold GARCH and developed by Glosten, Jagannathan and Runkle [34] also measures stylized facts such as the leverage effect and effect of the news on stock markets. In this model there is only regression in the mean equation which is constant:

$$ht = \delta + \alpha_1 e_{t-1}^2 + \gamma d_{t-1} e_{t-1}^2 + \beta_1 h_{t-1} \quad (4)$$

$$\sigma_t^2 = \omega + \alpha$$

where dt represents two cases in case of 1 and 0, where $et < 0$, creates bad news and 0, $et > 0$ indicates good news. Further the value of alpha, Gamma and Beta are non-negative parameters satisfying condition similar to the EGARCH model in an otherwise manner. In 1993 Ding, Granger and Engle introduced the Asymmetric Power ARCH Model known as APARCH which is an asymmetric model and perfectly expresses details of Fat tails, presence of leverage effect and leptokurtic effect. APARCH model expands as follows; APARCH model includes ARCH and GARCH model and by changing parameters, the result can also be abstracted for ARCH, GARCH, GJR, TAR, NARCH and Log-ARCH models.

INTERPRETATION, EMPIRICAL RESULTS AND DISCUSSIONS

Shanghai Stock Exchange Composite Index was introduced in December 1990 with a base index of 100 points over 30 years it has never traded below the base level. The paper includes data ranging from 19th December 1990 to 31st December 2020 considering 7494 daily closing observations. We parted data for the year 2020, i.e., January to June and July to December to compare high magnitude negative and positive changes. It provides interesting and lucrative outputs such as 100 low and 6092 lifetime high and low index trading levels. SSE Composite index movement shows constant upward trend between 2006 and 2007 escalating trading level from 1000 to 6000 which denoted as rapid and aggressive transmitting index movement pattern as high positive and negative shocks reported. Before the global financial crisis movement pattern. It is insightful to note the most aggressive series transmitting pattern for the Chinese stock exchange. Two strongest positive high magnitude shocks appear followed by negative continuous shocks correcting excess gambling trading. SSE Composite Index series movement rejects the hypothesis of financial theory for normal distribution as the series jumps from base 100 to above 6000 with the continuous escalation of a central point. By looking at the series movement, it appears attention to 2006, 2007, 2008, 2013, and 2014 which indicate the largest market growth and fall. Using log conversion and considering the first log-difference, the SSE China series is converted into stationary and reflects volatility clustering. Thus, it reviews earlier assumption that appears on actual series movement for higher magnitude shocks. Figure 2 provides information that high shocks follow several low shocks. Further, negative shocks with high magnitude follow several positive high shocks with low magnitude continuously for a prolonged period. It indicates volatility is clustering and makes a constant mean. This phenomenon attracts more loss and complex trading during the intra-day session. The property of descriptive statistics is summarized in table 1. The mean value is non-negative indicating a positive return and an increase in asset value over

time. From table 1 it is inferred that asset return is positively skewed with an exceptionally high degree of positive kurtosis. It creates a leptokurtic effect, makes a distinct peak near the mean and contains a probability of rapid decline (graphical presentation appears in figure 3). The statistical hypothesis of the normal distribution is three. In the present study, excess kurtosis indicates over 160 suggesting stock increases the probability of extreme events. This indicates that Shanghai Stock Exchange pertain probability for large numbers of unexpected and extreme events rises in the aspect of stock returns. It creates thicker tails and higher peaks. This read as highly speculation in asset prices during intra-day sessions.

Table 1

DESCRIPTIVE STATICS OF SSE COMPOSITE DAILY RETURNS FOR THE SAMPLE PERIOD DECEMBER 1990 – DECEMBER 2020			
Mean	Median	Minimum	Maximum
0.000438	0.0004	-0.17905	0.7191
Std. Dev.	Skewness	Ex. kurtosis	N
0.022	5.39	163.52	7490

Table 2

DESCRIPTIVE STATICS OF SSE COMPOSITE DAILY RETURNS FOR THE SAMPLE PERIOD JANUARY 2020 – DECEMBER 2020			
Mean	Median	Minimum	Maximum
0.000479	0.00071	-0.080	0.0555
Std. Dev.	Skewness	Ex. kurtosis	N
0.013	-0.98	6.99	241

The descriptive property indicates a strong positive skewed return indicating higher peaks at left-to-right. It implies extreme value on the left side of the mean are more likely than corresponding extreme value to the right side of the mean. Intra-day activity or movement of the index during exchange hours allows a high probability for extreme events with more positive side than negative. In an abridged way, stocks over and over yield high positive amounts and often charge negative shocks. The property of table 1 which provides a summary of statistics for 30 years indicates positively skewed returns with extremely high leptokurtic impact and a greater degree of standard deviations. The index has delivered over 60 times returns if considered the SSE index. However, the descriptive statically property of table 2 provides details only for the COVID-19 time frame and absorbs volatile changes for a period of 1 year, i.e. January 2020 to December 2020. It provides unexpected negative and positive shocks with negatively skewed returns and abnormal kurtosis. The comparative pattern of SSE China for 30 years and pandemic time appears in figure 2, provides evidence of strong negative magnitude, creating sudden

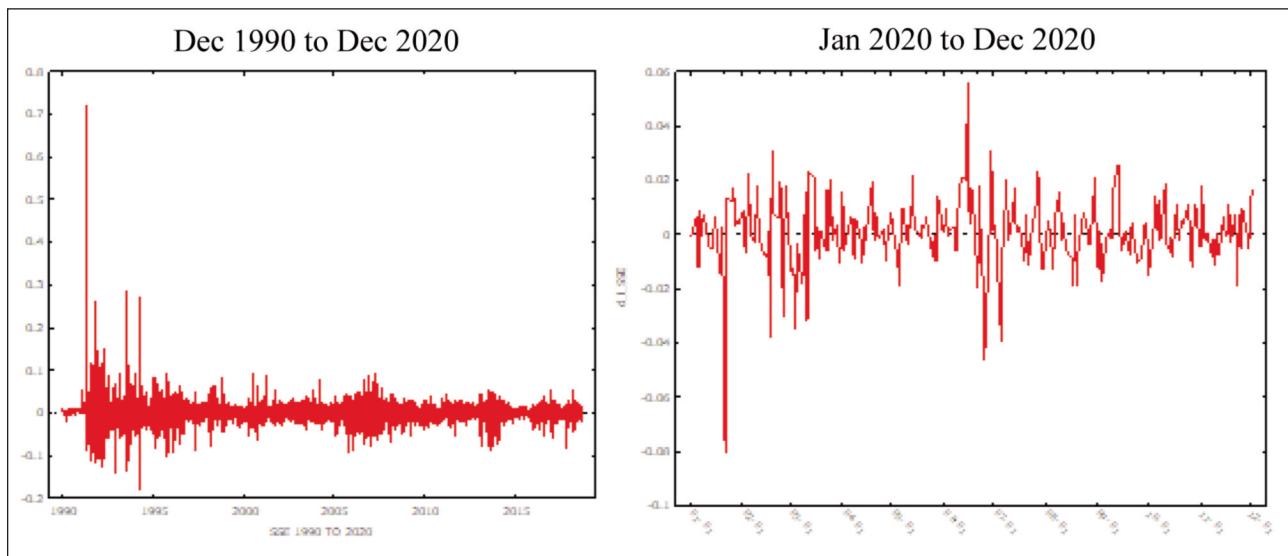


Fig. 1. Volatility shocks (stationary pattern) SSE China

fall and its recovery. The emerging period for SSE China financial markets i.e., 1990 to 1992 provided exceptional returns to early investors, and a few other major negative and positive shocks were observed in the first frame. The second frame provides two significant and contrasting movement pattern of the SSE index.

Table 3

RESULT OF ADF TEST (UNIT ROOT TEST) FOR RESIDUALS	
Value	AD F
t – statistics	–38.7308
Probability	0.000
A I C	–34299.5
B I C	–34258.2
H Q C	–34285.3

Baseline result of table 3 shows the presence of unit root in the series tested using the Augmented Dickey-Fuller test [35]. The probability value <0.05 ensures the time series for the entire study is stationary. ADF result property inferred volatility clustering in series returns of Shanghai Stock Exchange Composite Index. The study now focuses on the application of GARCH family models to find the best fit using student's t distribution and skewed t distributions. Property of table 4 indicates the result of GARCH (1, 1), EGARCH (1, 1) GJR GARCH and APARCH reveals parameter significant at 1% in case student's t distribution for entire series return (mean and variance equations both). Whereas the property of the mean equation is significant at 5% using skewed t distribution, the rest property of the variance equation is significant at the level of 1%.

Considering high and floating volatility in the Shanghai Stock market based on selected time variables, the statistical property of asymmetry GARCH

models confirms the presence of leverage effect (asymmetry) at a significant level of 1% indicating stock over-reacts during negative movement than positive movement. Further, it indicates that mean returns are merely zero and a high degree of standard deviations that make the market difficult to predict even during intra-day trade activity. Summary of statistics indicates that there is a high probability of loss transaction during day trading activity.

Application of GARCH and GARCH type model based on Student's t distribution and Skewed t distribution where the application of GARCH and GARCH type model fitted better in comparison to skewed distributions. Across all GARCH class models, APARCH with student's t distribution estimates the highest value for β , and best fit, while compared to BIC value criterion, followed by APARCH, skewed t distributions.

COVID-19 pandemic shock to the world economy impacted the SSE Composite index which appears to start from January 2020, the pandemic created unexpected and extended magnitude changes in asset returns. The novel outbreak has been declared a global pandemic by WHO and to prevent its spread, most of the economic activities have been significantly limited across the world. Detailed observation of the following charts indicates volatility reaction in Shanghai Stock Exchange, which reacted abnormally during the pandemic period i.e., March 2020 to June 2020. Despite news that started to appear in December 2019, there is no evidence on the SSE market until after a couple of sessions from January 2020. The first sudden reaction made SSE slip from the level of above 3100 to trade below 2700. Nevertheless, the second major negative movements appeared not until the index mostly recovered from the previous fall i.e. (January first negative movements). The second negative movements have made SSE China new low and escalated fears amongst the investors. Interestingly and very aggressively the

PROPERTY OF GARCH FAMILY MODELS					
GARCH (1, 1)					
Student's t distribution			Skewed t distribution		
Variable	Coefficient	z Statistic	Variable	Coefficient	z Statistic
Mean	0.0006	4.338 (1%)	Mean	0.00038	2.328 (5%)
Ω	4.99471e-06	3.579 (1%)	Ω	5.2256e-06	3.637 (1%)
α	0.152	5.998 (1%)	α	0.153668	6.099 (1%)
β	0.88	40.75 (1%)	B	0.877	45.57 (1%)
BIC:	-42192.74		BIC:	-42190.24	
EGARCH (1, 1)					
Student's t distribution			Skewed t distribution		
Variable	Coefficient	z Statistic	Variable	Coefficient	z Statistic
Mean	0.0006	2.932 (1%)	Mean	0.00037	2.11 (5%)
Ω	-0.3150	-6.543 (1%)	Ω	-0.3213	-6.690 (1%)
α	0.2389	9.713 (1%)	α	0.259810	9.912 (1%)
β	0.9820	211.2 (1%)	β	0.9815	211.3 (1%)
γ	-0.0413798	-4.486 (1%)	γ	-0.403788	-4.379 (1%)
BIC:	-42271.04		BIC:	-42267.98	
GJR					
Student's t distribution			Skewed t distribution		
Variable	Coefficient	z Statistic	Variable	Coefficient	z Statistic
Mean	0.0006	4.030 (1%)	Mean	0.00036	2.214 (5%)
Ω	5.27697e-06	3.744 (1%)	Ω	5.43186e-06	3.812 (1%)
α	0.153111	6.322 (1%)	α	0.155646	6.415 (1%)
β	0.874500	41.49 (1%)	β	0.872296	41.52 (1%)
γ	0.112353	4.343 (1%)	γ	0.107221	4.131 (1%)
BIC:	-42198.40		BIC:	-42194.72	
APARCH					
Student's t distribution			Skewed t distribution		
Variable	Coefficient	z Statistic	Variable	Coefficient	z Statistic
Mean	0.0006	3.728 (1%)	Mean	0.00041	2.406 (5%)
Ω	6.03562e-06	3.857 (1%)	Ω	6.22662e-06	3.894 (1%)
α	0.1319	8.165 (1%)	α	0.1336	8.148 (1%)
β	0.8960	59.96 (1%)	β	0.8944	58.98 (1%)
γ	0.1339	4.524 (1%)	γ	0.1281	4.311 (1%)
δ	0.9858	11.75 (1%)	δ	0.9935	11.80 (1%)
BIC:	-42275.85		BIC:	-42272.37	

SSE financial market movement appears strongly positive soon starting in July 2020. Further, the index remained traded between 3200 to 3500. In October 2008, the Shanghai Stock Exchange (Composite Index) faced a major impact on GFC, resulting in index trading almost greatest loss from its earlier trading level.

Two different frames appear in figure 3 providing observation for movement pattern during the pandemic period, in case assumed probably for January 2020 to June and July 2020 to December 2020, index movement observation indicates normal pattern even in January 2020 despite popularity news already appeared. The sudden negative fall appears on the first trading day of February 2020, the market opened

over 10% below than previous day opening approaching the index 321 points down and at the level of 2716 compared to the last trading day of January 2020 where the index opened at 3037. On the next trading day i.e., 4th February 2020, the index traded at 2685 and that remained the lowest trading level throughout the pandemic time. In the following 13 trading days, the SSE Composite index approached the index level of 3000 points. And regained previous loss. For the following trading days of March, April, May and June the index did not create a new low trading level either new high level i.e., above 3100 as closing or opening. The fall slop that appears during the months of February 2020 and Mar 2020 impacted a loss of over 400 index points

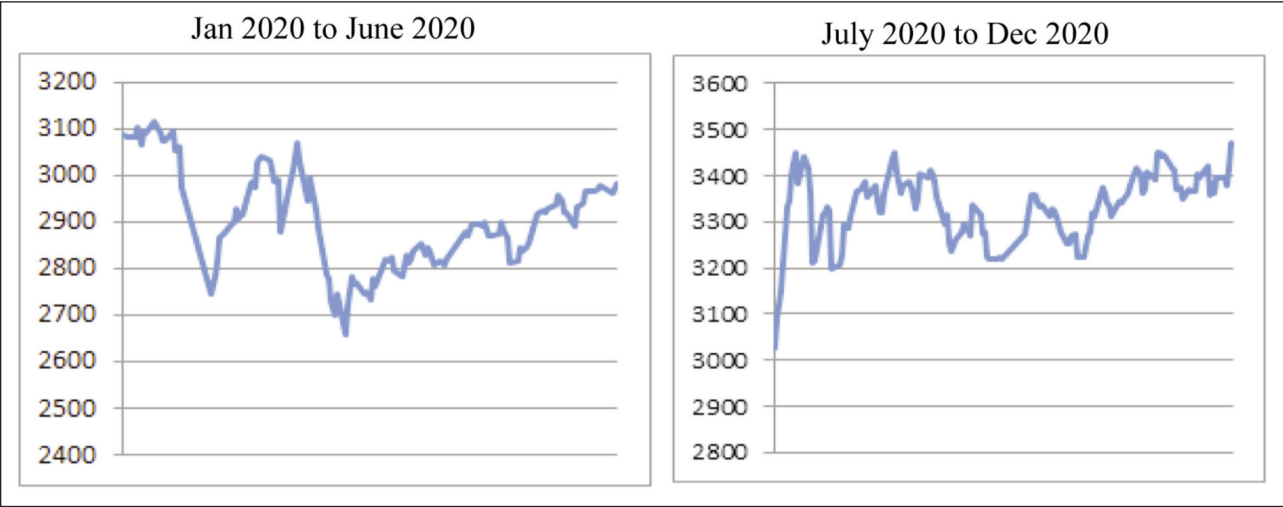


Fig. 2. SSE China – the pre and post-impact of COVID-19 pandemic

accounting for over 10% in just a few days. Further, the index recovered over 300 points which is again over 11% from the trading level of 2700, and breached the level of 3050, until retail investors restart investing. Surprisingly the index created a minor fall i.e., about 140 points and sustained a level of 3060 before the second sharp fall. This incident has impacted huge losses for the retail investors as the moments were entirely unpredictable. Steady and slow recovery of loss appears from the first week of April 2020. We evident the aggressive movement of the financial market starting with July 2020, also found the same aggressiveness to recover financial losses at the time of the Global Financial Crises of 2008.

The global financial crisis impacted entire economies of the world (including SSE – China) and has dramatically collapsed all economic stability across the countries. However, considering the collapse of the Chinese stock market (figure 1) provides evidence that Shanghai Stock Exchange is aggressively capable to recover from financial losses that occurred

during the last GFS. Further considering the present pandemic situation, the Chinese Stock Exchange (SSE), has recovered and re-established financial stability as an immediate start with the month of July 2020. It is not only about the financial markets, many researchers and scholars have captioned those financial markets at some point in economic activities and growth. However, it may not be absolute applicable to all economies. At present, China supplements equipment in various sectors across the world. Compared to the recovery process from the financial crisis, the first which appears in figure 3, at the time of 2005 (June and July) and in the second graph appears in figure 3, the movement of recovery of the financial market after the global financial crisis. The movement indicates the aggressiveness of recovery from 3000 index points to exceeding over 6000 within the period of one year. It indicates that the SSE – China reacts strongly to recover from the news-based financial impact.

Since the panic of lockdown and major economic damage across the world, China remained one of the

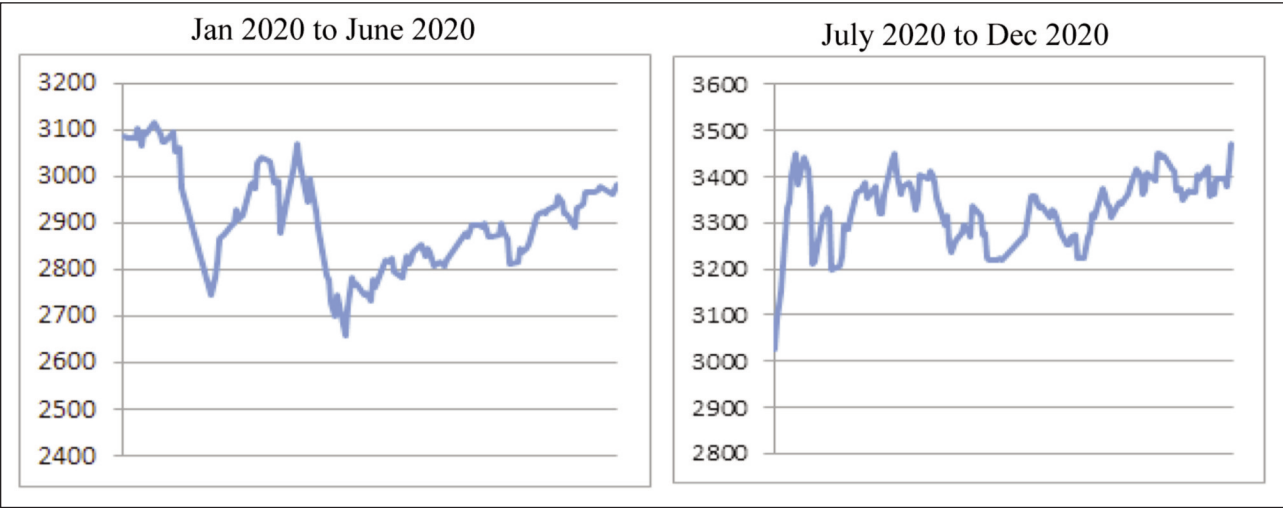


Fig. 3. SSE China January to December 2005 and January 2007 to January 2008 movement patterns

suppliers of medic and medic-related goods. The above graph indicates an abnormal rise for the SSE Composite index particularly starting in July and August. The index traded above 500 points more than the previous low of 2685 and created a new high instead of any negative movement. An interesting recovery that boosted up with strong positive shocks, which even higher degree of magnitude than the earlier negative shock (see figure 1). The SSE index trading at the level of 3000 points at beginning of July 2020, escalated to 3400, making over 10% movement in sudden and aggressive scale, approaching making new high even before pandemic levels. The pandemic of COVID-19 impacted the sample Chinese market SSE Composite index possibly for only the two highest magnitude shocks that were observed in the month of February and repeated negative and more frequent positive shocks in the month of April, May and June.

CONCLUSIONS

An empirical study on Shanghai Stock Exchange applying symmetric and asymmetric GARCH and GARCH type models explored volatility and volatility clusters in series returns. The study finds a high to extremely high presence of volatility particularly from January 2020 to December 2020 and reported the presence of leverage effect, highly unpredictable market movement during day trading, over exceeding kurtosis (160) and risky returns as over twice movement between a high and low range of the trading index. Shanghai Stock Exchange indicates a high volume of gambling transactions that escalates volatility to an additional level and makes the stock market even more difficult to predict for artificial intelligence software.

The movement pattern of the Shanghai Stock Exchange found high volatility during prolonged periods with unpredictable high and low magnitude shocks. It probably provides a shocking experience during intra-day trading. Volatility sketches indicate that high magnitude shocks do not create continuous

following impact. However, negative shocks with high magnitude attract further negative shocks in continuation with comparative low magnitude. Statistical property of summary of statistics provided mean return merely to zero indicating investor's asset valuation either with least profit or lower than the purchase value. Findings of this study prove that bad news has a greater impact on financial markets compared to any good news as Sun and Yan [24], and Gan [25] found and indicated that daily returns exist in leverage effect and negative information shock remains greater.

The degree of standard deviation found (0.22) for the entire study period and (0.13) for the pandemic period, along with positively skewed over (5.39) for the entire study period and negatively skewed return for January 2020 to December 2020. This indicates market reacts to unpredictable positive shocks particularly when it is not expected. It impacts not allowing investors to reserve their profits. Further, it also creates a strong positive skewed pattern moving from left to right with some high positive shocks that creates a market more lucrative to investors. Symmetric GARCH (1,1) provides high volatility and persistence in volatility. Asymmetric GARCH models (EGARCH, GJR, APARCH) indicate the presence of leverage effect (asymmetry) in series returns of the Shanghai Stock Exchange. Statistical property of GARCH and GARCH type models significant at the level of 1% except for mean return by (skewed t) distribution significant at the level of 5%. APARCH model with student's t distributions was found to be the best model to estimate the volatility of pandemic time-varying volatility.

The dynamics of stock markets are important in the context of financial opportunities based on the international diversification of the portfolio. For instance, attracting foreign investors in China represents a possibility to improve the negative effects of the recent health crisis. Improving the innovation capability of China also plays a key role in recovering from losses caused by the COVID-19 pandemic.

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