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Post Economic Crisis Equity Market Analysis: Evidence from Indian, Sri Lankan and Pakistani Stock Index

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Abstract

This study analyzes the volatilities and return series of South Asian equity markets and compared them to the U.S. equity market. GJR-GARCH model with conditional mean is used to estimate the volatility of equity market returns of S&P BSE SENSEX(India), CSE All Share (Sri Lanka), KSE 100(Pakistan) and S&P 500 (U.S.). The sample period is from January 2000 to December 2019 and subperiods of pre-crisis from January 2000 to December 2007 and post-crisis from January 2001 to December 2019. The results show the evidence of persistent autocorrelation effect from Sri Lankan, Pakistani and Indian market in pre-crisis while U.S. market do not show the autocorrelation effect. Sri Lankan and Pakistani market consistently show persistent autocorrelation in post-crisis. The analysis finds the presence of volatility clustering in South Asian markets is weak compared to the U.S. market during pre-crisis, but it became stronger during post-crisis. It also finds that the ARCH effect reduced in post-crisis, while the leverage effect increases from all markets that implies the markets became more sensitive to the bad news and less sensitive to the good news. Indian market appears to behave like the U.S market while Sri Lankan and Pakistani markets are more volatile to the market information in terms of returns and volatilities.

Keywords: GJR-GARCH, Volatility clustering, Autocorrelation, (G)ARCH effect

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1. Introduction

Analysis of stock returns and associated volatilities are one of the ongoing topics for researchers and practitioners. As globalization has resulted in integration of financial markets around the world, the analysis of financial market has researched by number of scholars and market participants. Equity markets in South Asia are not alone in this as Withanage (2017) found Sri Lanka, Pakistan and India are interconnected. This phenomenon is due to the interdependence of equity markets among countries. South Asian economies have been growing rapidly as well as equity markets. Equity markets tend to grow as
economic size expands. As equity markets are considered leading indicators, understanding the equity markets makes it possible to predict and explain the economy. Jahfer and Inoue (2014) examined the relationship between stock market and economic development in Sri Lanka and found the existence of long-run association and confirmed key role of stock market in economic growth.

In addition to the relationship between economic growth and equity markets, globalization made each sovereign economy interdependent. This implies the analysis of volatilities of equity markets become more important for policy makers to handle financial issues as well as for economic leaders to plan the growth of the economy as the relationship between financial markets and economies across countries getting stronger.

There is significant number of papers on equity markets in South Asia, but due to the size of the markets compared to larger emerging and developed economies, studies on South Asian markets are outnumbered by emerging and developed markets. Even with number of studies conducted on risk analysis in South Asian equity markets, empirical research on volatility comparison with developed market is limited. Thus, this study mainly focuses on exploring the characteristics of equity markets in South Asia by analyzing the equity market returns and volatilities. Moreover, the study compares stock markets in India, Sri Lanka, and Pakistan with U.S. equity market. The study will employ GJR-GARCH model and interpret the response of GARCH and ARCH effect of each market during pre-economic crisis in 2007 and post-crisis as well as the entire period. The contribution of this study is significant because investment strategy can be built on the relationship between the U.S. market and the South Asian markets and comparison of the volatility characteristics will help strategize the investment for different economic status.

The rest of this paper will be outlined as follows. Section 2 will provide a brief survey of relevant literature. Section 3 will state the objectives of this study and Section 4 will contain data and methodology with econometric models employed to explore the issue. Empirical results will be reported and discussed in section 5 followed by conclusion in section 6.

2. A brief survey of literatures

There have been numerous studies on volatilities and economic factors in relation to volatilities.

Narayan et al. (2004) examined stock market linkage using a temporal Granger causality approach. In the study, they bound the relationship among the stock markets of Bangladesh, India, Pakistan and Sri Lanka within a multivariate cointegration framework. They found that, in the long run, stock market in Pakistan is Granger-caused by the other three stock markets. They also found Granger-casualty between countries in short run.

Lamba (2005) investigated the short- and long-run relationships between south Asian markets of India, Pakistan and Sri Lanka and the major developed markets. Multivariate cointegration framework and vector error-correction model found the Indian market is persistently influenced by the major markets such as US. UK and Japan while Pakistani and Sri Lankan markets are relatively isolated. These three South Asian equity markets are found to be becoming more integrated with each other.

Tahir et al. (2013) investigated the interdependence among the South Asian and developed markets using correlation matrix, unit root, cointegration test and Granger casualty. The study found no significant relationship between the South Asian and developed equity markets, but US and India found to be correlated. The Equity Markets of South Asia and Developed countries are not cointegrated with each other consistent with Lamba (2005).

Eryilmaz (2016) examined the financial market structure by analyzing the relationship between stock volatility and trading volume of Bangladesh, India and Pakistan using Granger Causality Analysis. The paper is investigating the stock markets from different angles as well as examining relationship between economic factors and equity markets.

These studies above are examining the stock market with returns and volatilities. As volatility is not directly observable, researchers used standard deviation of return series as a proxy of volatility. Although the studies assumed constant volatilities, it is widely accepted that the volatilities vary over time among the researchers and practitioners.

The introduction of autoregressive conditional heteroskedasticity model (Engle, 1982), known as ARCH, and later developed to Generalized ARCH (Bollerslev, 1986) is efficiently estimating the time varying volatilities. One of the characteristics of the time varying volatility is clustering around itself. (Engle, 2001) After the development of the GARCH, researchers and practitioners have adopted the model to describe and interpret the volatilities of financial markets. There has been enormous amount of research with ARCH/GARCH and even other form of GARCH models such as EGARCH (Nelson 1991), GJR-GARCH(Glosten et al 1993) and IGARCH(Engle and Bollerslev 1986).

There are notable papers on volatilities with GARCH family in South Asian markets.

Vasudevan (2016) forecasted volatility of Indian stock market using symmetric GARCH(1,1), and asymmetric GARCH, such as EGARCH(1,1) and threshold-GARCH(1,1). The study found asymmetric GARCH performs better than symmetric GARCH in forecasting the market and confirmed the presence of leverage effect.

Nassem et al. (2018) conducted empirical analysis of Pakistani equity market using various GARCH-type models and confirmed leverage effect from the return series. They employed symmetric GARCH and asymmetric GARCH models to examine the leverage effect of the market and found EGARCH with student-t distribution performs the best.

Asif et al. (2016) investigate the cluster volatility of the Pakistan Stock market return distribution using GARCH-type models, such as GARCH, EGARCH, PGARCH and TARCH models. In this study, they found GARCH(1,1) to be the most appropriate among the models examined and explained the cluster volatility and leptokurtic distribution.

Akhtar and Khan (2016) analyzed Pakistani market during pre-crisis and post-crisis using GARCH family, such as GARCH, GARCH in mean, EGARCH, threshold-GARCH, power-GARCH and exponentially weighted moving average (EWMA) model. The study found return series to be non-normal, volatility clustering and significant leverage effect of the market. The study also found P-GARCH (1, 1) performs better in modeling daily volatility, while the GARCH (1, 1) model works better for weekly returns.

Jegajeevan (2010) examined the Sri Lankan stock market using different GARCH models to find presence of asymmetric volatility as well as high persistent GARCH effect from daily returns but found no existence of ARCH effect from monthly returns.

Morawakage and Nimal (2015) used GARCH, EGARCH and TGARCH to capture volatility characteristics and observed that volatility clustering and leverage effect exists in Sri Lankan stock market. They also found negative shocks create more volatility compared to positive shocks generated in the market.

3. Objectives of the Study

The main purpose of this study is to investigate the changes in volatility characteristics of stock market from pre-economic crisis to post-economic crisis.

The study is designed to

1. Estimate the volatilities of South Asian equity markets and compare characteristics of the volatilities to those of U.S. market.

2. Examine the changes in characteristics of the volatilities from pre-crisis period to post-crisis period.

4. Data & Methodology

The data used in this study are the daily stock indexes for three South Asian countries and the U.S. market as a benchmark from January 2000 to December 2019. The data consist of the Bombay Stock Exchange Sensitive Index (India), Colombo Stock Exchange All-Share

Index (Sri Lanka), Karachi Stock Exchange 100 (KSE 100) Index (Pakistan) and S&P 500 (U.S.). The data have 2 sub-periods to investigate the different impact of the stock market; pre-Crisis ranges from January 2000 to December 2007 and post-Crisis from January 2008 to December 2019. In the stock market, volatility is an indicator that measures the degree of stock return fluctuation around the average. It plays a very important role not only in the theoretical model in financial management but also in practical areas such as portfolio optimization, securities price evaluation and risk management. Engel (1982) first created an econometric model for the volatility, Autoregressive Conditional Heteroscedasticity (ARCH). The ARCH model is known to capture the characteristics of returns and volatilities observed in the stock market.

The conditional variance in the ARCH model is designed to be affected by the square of the error term in the past by increasing the lag. However, as the error term in the ARCH model cannot be estimated by increasing the lag to infinity, Bollerslev (1986) generalized the model (GARCH) by adding past conditional variance term as:

$$r_t = \beta_0 + \sum_{j=1}^{n} \beta_j r_{t-j} + \varepsilon_t$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 \sigma_{t-1}^2 + \gamma_2 \varepsilon_{t-1}^2$$

Where, r_t is the return at time *t,* σ_t^2 is conditional variance at time *t,* ε_t^2 is error term and a square root of the conditional variance is defined as volatility.

The model is designed to make volatility of the present return depend on variance of current error term in the return model and the volatility of the past, so the thick-tailed distribution of returns and cluster characteristics of volatility are well expressed in the model. One of the characteristics of stock returns is the existence of leverage effect that volatility respond asymmetrically to positive and negative shocks. However, since volatility is designed to respond symmetrically to market shocks in the GARCH model, it does not reflect the asymmetry of volatility, in which the increase in volatility when the rate of return falls is greater than the extent of the decline in volatility when the rate of return rises, the leverage effect. EGARCH (Nelson, 1991) and GJR-GARCH (Glosten et al., 1993) are the most used models to handle the leverage effect.

The study analyzed the GJR-GARCH model to allow the asymmetric response of volatility to both positive and negative shocks. For this study, daily index returns are obtained by taking the logarithmic difference of daily stock index as

$$r_{i,t} = log_e S_{i,t} - log_e S_{i,t-1}$$

Where, $S_{i,t}$ is the value of index *i* at time *t*. The GJR-GARCH(1,1) with conditional mean (Autoregressive) model employed in this study is defined as follows:

$$r_{i,t} = \beta_{0,i} + \sum_{j=1}^{n} \beta_{j,i} r_{i,t-j} + \varepsilon_{i,t}$$

$$\varepsilon_{i,t} = \sigma_{i,t} z_{i,t}$$

$$\sigma_{i,t}^2 = \gamma_{0,i} + \gamma_{1,i}\sigma_{i,t-1}^2 + \gamma_{2,i}\varepsilon_{i,t-1}^2 + \gamma_{3,i} I_{i,t-1}\varepsilon_{i,t-1}^2$$

$$I_{i,t-1} = \begin{cases} 1 \ \ if \ \varepsilon_{i,t-1} < 0 \\ 0 \ \ if \ \varepsilon_{i,t-1} \geq 0 \end{cases}$$

Where, $r_{i,t}$ is the log return at time *t* of index *i*, and *n* is determined by the significance of autocorrelation of the returns. $\sigma_{i,t}^2$ is conditional variance at time *t* of index *i*, and $I_{i,t-1}$ is a dummy variable at time *t*-1 taking 1 if the shock ($\varepsilon_{i,t-1}$) is negative (bad news) and 0 if positive (good news). That is $\gamma_{2,i}$ is coefficient of positive shock, and $\gamma_{2,i} + \gamma_{3,i}$ is coefficient of negative shock. Thus, $\gamma_{3,i} > 0$ implies that the effect of bad news has greater impact on the conditional volatility than good news. This will allow us to examine the impact of different news at time *t*-1 on the volatility at time *t*. In this GARCH-type model, $\sigma_{i,t-1}^2$ term is referred to as GARCH effect and $\varepsilon_{i,t-1}^2$ term as ARCH effect.

The model in this study is estimated using maximum likelihood estimation to maximize the log-likelihood (LL) function.

$$LL_T = -\frac{1}{2}\sum_{i=1}^{T}\left[\ln(2\pi) + \ln(\sigma_t^2) + \frac{\varepsilon_t^2}{\sigma_t^2}\right]$$

The study analyzes the returns and the volatilities to compare the characteristics of each market in South Asia to US market during pre-crisis period and post-crisis period and interpret how the markets have changed from pre-crisis to post-crisis. It also studies the long-run characteristics of the markets by investigating the entire period from January 2000 to December 2019.

5. Empirical Result

Table 1 reports average return, volatility, Sharpe ratio, skewness, excess kurtosis, Jarque-Bera normality test, autocorrelations and Ljung-Box Q-test for autocorrelation to understand the nature of each stock market returns across countries.

For the entire period, all three South Asian stock markets generate significantly higher return than the U.S. market. Indian market generated 10.39% with 0.4564 Sharpe ratio that is the lowest among the three indexes, and Pakistani market has the highest return and Sharpe ratio among three, 16.9% and 0.7968, respectively. The higher momentum shows some degree of skewness and kurtosis for all indexes including U.S. market and Jarque-Bera normality test rejects the hypothesis that the return series are normally distributed for all indexes at 1% significance level. The autocorrelation shows high persistence in South Asian markets compared to U.S. market. India has significant autocorrelation coefficient on lag 1, 2, and 9, Sri Lanka has lag 1, 4, 7, 10 and Pakistan has lag 1, 2, 3, 5, 7, 9, and 10 while U.S. market has lag 1, 2, and 5. Ljung-Box Q-statistics reject the non-existence of autocorrelation hypothesis suggesting that daily returns of indexes are serially correlated.

The subperiods show slightly different story from the entire periods. Sri Lanka and Pakistan generated 19.94% and 28.81% average return during pre-crisis that are higher than those of the entire periods, but with higher volatilities. These returns go down by more than 60% during post-crisis. This implies that the global economic crisis started at the end of 2007 affected the South Asian market more than it did the U.S. market.

There are a few characteristics need to be addressed. First, all stocks markets during pre-crisis show higher returns than those during post-crisis as well as the Sharpe ratios. Indian and U.S. stock market returns do not show statistically significant from zero in pre-crisis, and Sri Lankan and Pakistani stock markets are significantly greater than zero. Indian market is considered relatively larger market than Sri Lankan and Pakistani markets and it tends to have similar market behavior as the U.S. market; returns are not significant in Indian market and U.S. market and autocorrelation of Indian market during post-crisis decrease to only one lag.

Second, skewness and high excess kurtosis suggest the presence of significant positive and/or negative shocks. Sri Lankan market show very high excess Kurtosis of 29.7 suggesting significantly high return shocks during pre-crisis.

Third, the return series show high persistence for longer lags for all periods except for post-crisis Indian market. The reason that the South Asian stock markets have higher persistence might be due to the price band each stock market imposed on daily stock price movements. Ljung-Box Q statistics up to the 10th order for squared return series evidently show high dependency of volatilities suggesting ARCH/GARCH specification be appropriate modeling volatilities for the markets.

To investigate the return and volatility, the study jointly estimated Autoregressive conditional mean with GJR-GARCH, as the markets present high autocorrelation and high dependency of volatilities and Table 2 presents the results.

As noted, it appears that all three markets have longer lags except for post-crisis Indian market. It shows that all the autocorrelated return series are positively correlated except for the lag 8 of pre-crisis Sri Lankan market. Sri Lankan and Pakistani markets have increased number of orders of autocorrelation during post-crisis while Indian market decreased to only one order implying persistent influence of prior information on returns in Sri Lankan and Pakistani market. The relatively higher AR(1) coefficient (β_1) of 0.1977 in Sri Lankan market and 0.1915 in Pakistani market in post-crisis implies high market momentum suggesting the forecasting of the market high depends on recent market information. Considering the size of Indian market significantly larger than Sri Lankan and Pakistani markets, it seems that the market behaves the U.S. market does during the post-crisis according to the AR process.

The estimates from GJR-GARCH indicate that most of the parameters are statistically significant and considerably larger GARCH effect than ARCH effect suggests the forecasting volatility is dominated by lagged volatility. This is consistent with Jegajeevan's (2010) finding implying the presence of volatility clustering. During pre-crisis, the GARCH effect from India, Sri Lanka and Pakistan show 0.7885, 0.5821 and 0.7267 that are lower than that of U.S. market, but rose to 0.9128, 0.8326 and 0.8129 similar to U.S. market. This larger effect of GARCH process indicates the shocks from lagged volatility takes more time to diminish the effect, the GARCH coefficients during post-crisis show the volatility became more volatile than pre-crisis for all South Asian markets while U.S. market's GARCH coefficient decreased. This also suggests the old information still significantly influences the South Asian markets more during post-crisis than pre-crisis. South Asian markets, as smaller markets than the U.S. market, show more volatile market behavior when going through the economic crisis.

On the other hand, the markets show reduced ARCH effect suggesting past positive shocks induce relatively small volatility. Market participants became more dependent on the past volatility information than the positive market surprise in assessing the risk during post-crisis.

In Sri Lankan market, ARCH effect decreased by more than 50% for the positive shocks. It is also noted that pre-crisis Indian market does not appear to have statistically significant ARCH effect on positive shocks. U.S. market shows no ARCH effect on market surprise for the entire period. During the pre-crisis, Indian market shows γ_3 of 0.2489 on negative shock, that is the highest among the equity markets in the analysis but decreases by 50% during post-crisis. Indian market is the only market with reduced leverage effect from pre-crisis to post-crisis. This implies that negative market information contributed to the volatility more in pre-crisis, but the market became to depend more on the recent volatility information than market information in post-crisis.

It is noted that Indian market, as the U.S. market, does not show ARCH effect on positive shocks in pre-crisis. During post-crisis, Indian market appears to have ARCH effect on both positive and negative shocks. Sri Lanka does not show leverage effect for the entire period meaning positive and negative shocks have the same impact on the volatility, but it appears to have leverage effect while going through the economic crisis; it shows statistically significant leverage effect in post-crisis.

Sri Lankan market show significantly high ARCH effect on shocks, 0.4212, in pre-crisis, but does not show evidence of leverage effect. This ARCH effect is reduced, in post-crisis, to 0.1369 on positive and 0.1801 on negative shock. Not like the GARCH effect that all three South Asian markets have increased in post-crisis, Sri Lankan and Pakistani markets have decreasing ARCH effect.

For Pakistani market, ARCH effect on positive shocks has decreased by 75%, but the leverage effect rose by 60% that implies Pakistani market still has high ARCH effect on negative shocks while the effect is very small on positive shocks. It shows that the ARCH effect on positive shock decreases from 0.147 in pre-crisis to 0.0353 in post-crisis, but the effect on negative shock rose from 0.2361 to 0.2801. Sri Lankan and Pakistani markets indicate that the markets became highly responsive to bad news during post-crisis. The U.S. market shows no ARCH effect on positive news both pre- and post-crisis, but the market appears to have increased leverage effect from 0.1259 in pre-crisis to 0.2360 in post-crisis. U.S. market became more sensitive to negative information during post-crisis.

Significantly high GARCH effect observed from all markets suggest the presence of volatility clustering South Asian equity markets and the presence of leverage effect implies the market are significantly impacted by the lagged bad news than good news. Though the impact of the leverage effect on Sri Lankan market is not as high as the other markets in post-crisis, the market still has significantly higher ARCH effect.

In addition, sum of the GARCH and ARCH coefficient being close to unity implies the persistent evolution of volatility for all markets throughout the periods suggesting persistent volatilities in South Asian equity markets.

6. Conclusion

We have investigated the returns and volatilities of South Asian markets and compared to the U.S. market. The study did not employ other methods than GJR-GARCH, such as GARCH or IGARCH because the main purpose was to estimate the volatility and to test the existence of leverage effect of the return series. The model was sufficient to capture the characteristics of the returns and volatilities and the South Asian markets exhibit significant leverage effect.

We also found the markets exhibit volatility clustering that is stronger during post-crisis period than pre-crisis. The similar GARCH effect and stronger volatility clustering among the three South Asian markets may be caused by more trading between the economies. The globalization resulted in growing South Asian equity markets and the markets became more integrated through the crisis as the economic impact influenced throughout the globe. South Asian markets are relatively small, and the impact of the economic crisis was larger than other developed countries, and the characteristics of market volatility changed as a result of the crisis.

As South Asian equity markets change their characteristics in volatilities, portfolio managers can adjust portfolio strategies according to the short-term impact or long-term persistence in each equity market. The study did not intend to identify the possible cause of it because the model employed in the study is not designed to capture the event. Identifying the cause of stronger volatility clustering can make it possible to understand linkage between equity markets in South Asia. Macroeconomic factors with multivariate model approach may be employed to identify the cause of the change and the study can broaden the research on the linkage between global economy and South Asian economy.

Table 1. Statistics of daily market returns (statistics presented on an annualized basis)

	Entire period: Jan.2000 ~ Dec.2019				pre-Crisis: Jan.2000 ~ Dec.2007				post-Crisis: Jan.2008 ~ Dec.2019			
	India	Sri Lanka	Pakistan	U.S.	India	Sri Lanka	Pakistan	U.S	India	Sri Lanka	Pakistan	U.S
Mean	0.1039*	0.1267*	0.169*	0.04	0.1669	0.1994*	0.2881*	-0.0011	0.0611	0.0786*	0.0899	0.065
	(2.0251)	(3.1433)	(3.5342)	(.9417)	(1.9285)	(2.4360)	(3.2452)	(-.0180)	(.9707)	(1.9954)	(1.6831)	(1.1555)
Volatility	0.2276	0.1744	0.2121	0.1881	0.2441	0.2235	0.2488	0.1763	0.2157	0.1322	0.1836	0.1956
Sharpe Ratio	0.4564	0.7265	0.7968	0.21	0.6835	0.8919	1.1581	0.0063	0.2835	0.5947	0.4896	0.3325
Skewness	-0.1867	0.3478	-0.2595	-0.2295	-0.6225	0.1813	-0.2889	0.0476	0.2332	0.6199	-0.2569	-0.3678
ex-Kurtosis	7.9909	35.0842	3.7263	8.6425	3.9968	29.7015	2.8488	2.5494	12.1493	11.8593	3.8833	11.1678
JB statistic	13124.1**	240119.7**	2900.5**	15695.3**	1453.1**	68562.8**	691.1**	544.8**	18059.2**	16676.6**	1889.3**	15762.1**
ACF												
ρ_1	0.0763*	0.1665*	0.1008*	-0.0741*	0.0724*	0.1634*	0.042	-0.0394	0.0793*	0.1713*	0.1672*	-0.0932*
ρ_2	-0.0343*	0.0106	0.0318*	-0.0529*	-0.0422	-0.0526	0.0102	-0.0421	-0.0277	0.1292*	0.0532	-0.0589*
ρ_3	-0.0257	0.0191	0.0336*	0.0225	-0.0039	-0.0168	0.0539*	-0.0048	-0.0453	0.0857*	0.0126	0.0363
ρ_4	0.0028	0.0303*	0.016	-0.017	0.066*	0.0051	-0.0078	0.0064	-0.0528	0.0771*	0.0466*	-0.02
ρ_5	-0.0257	0.0056	0.0307*	-0.0426*	-0.0209	-0.0055	0.0237	-0.028	-0.0307	0.0252	0.0379	-0.0516*
ρ_6	-0.0241	-0.0019	0.0115	0.0037	-0.0554*	-0.0165	-0.0095	-0.0316	0.0025	0.025	0.0357	0.0235
ρ_7	0.0221	0.0305*	0.0307*	-0.0206	-0.0042	0.0149	0.0432	-0.033	0.0435	0.0593	0.0116	-0.014
ρ_8	0.0103	-0.0056	-0.0027	0.0115	0.0051	-0.047*	0.0261	0.0038	0.014	0.072*	-0.0411	0.0165
ρ_9	0.03*	0.0264	0.051*	-0.0088	0.0533*	0.0241	0.0936*	-0.0038	0.0097	0.0299	-0.0041	-0.0106
ρ_{10}	0.0227	0.0626*	0.038*	0.0207	0.0261	0.0492*	0.0246	-0.0011	0.0198	0.0872	0.053*	0.0313
$Q^2(10)$	1567.1**	509.5**	2250.6**	4162.4**	604.6**	168.8**	817.4**	744.2**	1038.8**	601.6**	1158.3**	2769.3**

- *t*-statistics are in parentheses. * and ** indicate statistically significant at 5% and 1%, respectively.

Table 2. Estimates of AR-GJR(1,1) GARCH model of daily stock returns

	Jan.2000 ~ Dec.2019				Jan.2000 ~ Dec.2007				Jan.2008 ~ Dec.2019			
	India	Sri Lanka	Pakistan	U.S.	India	Sri Lanka	Pakistan	U.S.	India	Sri Lanka	Pakistan	U.S.
Conditional Mean Model												
β_0	0.0004**	0.0001	0.0006**	0.0003*	0.0005	0.0005**	0.0011**	-0.0001	0.0003*	0	0.0003	0.0004**
	(2.8929)	(1.0198)	(4.0569)	(2.3932)	(1.7964)	(2.6914)	(3.4478)	(-.2745)	(1.9945)	(-.1362)	(1.9021)	(2.8620)
β_1	0.0914**	0.2546**	0.1281**	-0.0577**	0.1157**	0.2921**	0.0713**		0.0774**	0.1977**	0.1915**	-0.0602**
	(5.8460)	(20.2996)	(8.5197)	(-3.7942)	(4.6228)	(13.5724)	(2.8349)		(3.7292)	(9.2720)	(10.2617)	(-3.2455)
β_2	0.0408**	0.0239*	0.0364**	-0.033*	0.0749**	-0.039**	0.0818**			0.0831**	0.0505**	
	(2.9068)	(2.0047)	(2.6425)	(-2.3511)	(3.2443)	(-3.3521)	(3.7495)			(3.8440)	(2.7928)	
β_3		0.0484**	0.033*		0.0429*	0.046*				0.0414*	0.0537**	
		(3.8289)	(2.4827)		(2.1742)	(2.5597)				(2.0349)	(3.2182)	
β_4		0.0333**								0.061**		
		(2.7594)								(3.0496)		
β_5										0.063**		
										(3.6216)		
lags	(1, 9)	(1, 4, 7, 10)	(1, 9, 10)	(1, 5)	(1, 4, 9)	(1, 8, 10)	(3, 9)		(1)	(1, 2, 3, 4, 8)	(1, 4, 10)	(1)
Conditional Volatility Model												
γ_0	0.000003**	0.000003**	0.00001**	0**	0.000015**	0.000011**	0.000019**	0*	0.000001**	0.000001**	0.000005**	0**
	(6.3294)	(9.5598)	(37.5126)	(6.4459)	(10.0476)	(16.5233)	(9.4967)	(2.343)	(3.2095)	(3.8032)	(10.0130)	(6.227)
γ_1	0.8876**	0.7412**	0.79026**	0.88291**	0.7855**	0.5821**	0.7267**	0.9253**	0.9128**	0.8326**	0.8129**	0.8563**
	(158.7840)	(89.8320)	(100.4007)	(125.5079)	(51.8747)	(43.1228)	(29.7945)	(100.0566)	(131.6527)	(103.2633)	(81.2194)	(86.5335)
γ_2	0.0385**	0.2502**	0.09954**	0	0.0165	0.4212**	0.147**	0	0.0186**	0.1369**	0.0353**	0
	(7.8008)	(25.1248)	(11.7091)	(.0000)	(1.0434)	(17.8615)	(6.8884)	(.0000)	(3.8743)	(15.6902)	(4.5207)	(.0000)
γ_3	0.1216**	0.0172	0.1353**	0.18903**	0.2489**	-0.0065	0.0891**	0.1259**	0.1224**	0.0432**	0.2448**	0.2360**
	(12.4566)	(1.0701)	(9.0951)	(16.7446)	(7.7035)	(-.1611)	(3.4623)	(8.2021)	(10.1908)	(2.8880)	(10.9782)	(13.743)

- *t*-statistics are in parentheses. * and ** indicate statistically significant at 5% and 1%, respectively.
- The order of j in the conditional mean model for stock index I is based on the significance of autocorrelation as in Table 1. Insignificant terms are deleted during the estimation. The numbers in brackets indicate the order of AR. For example, for Indian stock index during the period Jan.2000 to Dec. 2019, the conditional mean model consists of AR(1) and AR(9).
- γ_0, γ_1, γ_2 and γ_3 are coefficients for constant, GARCH, ARCH and leverage effect, respectively.

References

Akhtar, S., & Khan, N. U. (2016). Modeling volatility on the Karachi stock exchange, Pakistan. *Journal of Asia Business Studies*

Asif, M., & Aziz, A. (2016). Equity market volatility using GARCH models-evidence from Pakistan stock exchange (kse-100 index)

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

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica: *Journal of the econometric society*, 987-1007

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

Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *Journal of economic perspectives*, 15(4), 157-168

Eryilmaz, F. (2016). Volatility and the Regulation of Stock Markets: Evidence from South Asia. *In Financial Market Regulations and Legal Challenges in South Asia* (pp. 134-145). IGI Global

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

Jegajeevan, S. (2010). Return volatility and asymmetric news effect in Sri Lankan stock market. Staff Studies, *Central Bank of Sri Lanka*, 40(1)

Jahfer, A., & Inoue, T. (2014). Stock market development and economic growth in Sri Lanka. *International Journal of Business and Emerging Markets*, 6(3), 271-282

Lamba, A. S. (2005). An analysis of the short-and long-run relationships between South Asian and developed equity markets. *International Journal of Business*, 10(4)

Morawakage, P. S., & Nimal, P. D. (2015). Equity market volatility behavior in Sri Lankan context. *Kelaniya Journal of Management*, 4(2), 112-117

Narayan, P., Smyth, R., & Nandha, M. (2004). Interdependence and dynamic linkages between the emerging stock markets of South Asia. *Accounting & Finance*, 44(3), 419-439

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, 347-370

Naseem, S., Mohsin, M., Zia-ur-Rehman, M., & Baig, SA (2018). Volatility of pakistan stock market: A comparison of Garch type models with five distribution. *Amazonia Investiga*, 7(17), 486-504.

Tahir, S. H., Sabir, H. M., Ali, Y., Ali, S. J., & Ismail, A. (2013). Interdependence of South Asian & developed stock markets and their impact on KSE (Pakistan). *Asian Economic and Financial Review*, 3(1), 16-27

Vasudevan, R. D., & Vetrivel, S. C. (2016). Forecasting stock market volatility using GARCH models: Evidence from the Indian stock market. *Asian Journal of Research in Social Sciences and Humanities*, 6(8), 1565-1574

Withanage, Y., & Jayasinghe, P. (2017). Volatility spillovers between south Asian stock markets: evidence from Sri Lanka, India and Pakistan. *Sri Lanka Journal of Economic Research*, 5(1)