TSME

Journal of Management

Volume 7, No. 2 July-December 2017 (ISSN 2249-6092)

A COMPARATIVE STUDY OF RISK AND RETURN OF INDIAN STOCK MARKET AND WORLD EQUITY MARKETS

Dr. Niti Goyal*

Dr. Anil K. Mittal**

ABSTRACT

This article aims at studying the stock price behaviour and modelling and comparing the volatility of Indian Stock Market with the world equity markets. It also investigates if there is any asymmetric volatility in the return structure. S&P CNX Nifty returns have been used to proxy the Indian Stock Market and returns of MSCI-ASWI index have been used to proxy global equity markets over the eight years period starting from Jan, 2010- 2018. The return series exhibit heteroskedasticity, volatility clustering and has fat tails. EGARCH (1, 1) model has been found to be appropriate model to capture the volatility. The ARCH in Mean model reported that stock markets do not offer risk premium. Apart from the presence of leverage effect, we also found that Indian stock markets provide better return per unit of risk but is informationally inefficient as higher volatility persistence has been found over the period considered.

Keywords: Volatility; GARCH, EGARCH.

INTRODUCTION

Volatility estimation helps in derivatives valuation, asset management and risk management and has many more financial applications. Volatility refers to the ups and downs in the stock prices. Volatility in the stock return is an integral part of stock market with the alternating bull and bear phases. One cannot earn superior returns without volatility. However, too much volatility indicates inefficiency of the stock market. Volatility indicates risk. Volatile returns may hurdle investment in small developing economies. It has an impact on business investment spending and economic growth through a number of channels. Moderate returns, high liquidity and low level of volatility is taken to be a symptom of a developed market. Low volatility is preferred as it reduces unnecessary risk borne by investors thus enables market traders to liquidate their assets without large price movements. Investment decisions are governed significantly by volatility apart from other interdependent factors like price, volume traded, stock liquidity, among many others.

Volatility estimation is important for several reasons: Investment decisions, as characterized by asset pricing models, strongly depend on the assessment of future returns and risk of various assets. The pricing of options is based on expected volatility of a security. Various linear and nonlinear methods by which volatility can be modelled have been developed in the literature and extensively applied in practice to describe the stock return volatility.

The distribution of financial time series shows certain characteristics such as:

1. Leptokurtosis, i.e. fat tails as compared to normal distribution.
2. Volatility clustering: Statistically, volatility clustering implies a strong autocorrelation in returns. Large changes tend to be followed by large changes and small changes tend to be followed by small changes.
3. Heteroskedasticity, i.e. non constant variance.

*Assistant Professor, (corresponding author), IGN College, Ladwa; E-mail: nsingh0001@gmail.com

**Reader, USM, K.U.K.; E-mail: mittal_anil_kuk@yahoo.com

Economic time series have been found to exhibit periods of unusually large volatility followed by periods of relative tranquility (Engle, 1982). In such circumstances, the assumption of constant variance (homoskedasticity) is inappropriate (Nelson, 1991). This requires models that are capable of dealing with the volatility of the market (and the series). One of the most prominent tools for capturing such changing variance was the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) models developed by Engle (1982), and Bollerslev (1986) respectively. Following the introduction of models of ARCH by Engle (1982) and their generalization by Bollerslev (1986), there have been numerous refinements of the approach to modelling conditional volatility to better capture the stylized characteristics of the data. The GARCH (1, 1) is often considered by most investigators to be an excellent model for estimating conditional volatility for a wide range of financial data (Bollerslev, Ray and Kenneth, 1992). The characteristics of the Nifty return series and MSCI ACWI Index are consistent with the above characteristics of financial time series.

The aim of this article is to track and model the volatility of Indian stock Market and compare it with the world equity market. Globalization has resulted into integration among the financial markets. MNC's operate in multiple countries and their performance depends on economic and political conditions over their areas of operation. In addition, professional investors can take better investment decisions by knowing the return and the risk structure of the markets for proper diversification of their investments. Higher volatility in particular markets also point towards some reforms that need to be taken by the policy makers for making markets more efficient.

REVIEW OF LITERATURE

Much of the literature is present on modeling the volatility of the individual markets alone . No sufficient literature is available on modeling the volatility of an economy against the world equity markets.

Kedar nath Mukherjee, R.K. Mishra (2005), investigated the long-term interlinkages among the Indian stock market with that of other developed as well as emerging countries and tried to explore the possibility of potential diversification benefits for foreign investors to participate in the Indian equity market using Engel-Granger test using data from January 1996 to June 2004. The study found that except in case of Indonesia, Malaysia, Philippines, Korea, Thailand and Greece, none of the developed as well as emerging countries among selected for study have reported long run integration with Indian stock market. Rousan Raya, AL-Khouri, Ritab (2005), attempted to investigate the volatility of the Jordanian emerging stock market using daily observations from Amman Stock Exchange Composite Index (ASE) for the period from January 1, 1992 through December 31, 2004. The nature of the time series suggested ARCH and GARCH models as the best to capture the characteristics of ASE. Also no asymmetry was found in the returns and hence, both good and bad news of the same magnitude have the same impact on the volatility level. Moreover, the volatility persists in the market for a long period of time, which makes ASE market inefficient; therefore, returns can be easily predicted and forecasted.

Alberg et al. (2006) estimated stock market volatility of Tel Aviv Stock Exchange indices, for the period 1992-2005, using asymmetric GARCH models. They reported that the EGARCH model is most successful in forecasting the TASE indices. Banerjee Ashok & Sahadeb Sarkar (2006), attempted to model the volatility in the daily return in the Indian stock market. They found that the Indian stock market experience volatility clustering and hence GARCH-type models predict the market volatility better than simple volatility models, like historical average, moving average, etc. They also observed that the asymmetric GARCH models provide better fit than the symmetric GARCH model, confirming the presence of leverage effect. They also found that the change in volume of trade in the market directly affects the volatility of asset returns & the presence of FII in the Indian stock market does not appear to increase the overall market volatility.

Bhaskkar Sinha (2006) in an attempt to model stock market volatility of Indian markets and to capture the asymmetric effects found EGARCH model best for modeling volatility clustering and persistence of shock at BSE sensex and GJR-GARCH for NSE nifty. Debjiban Mukherjee (2007) investigated the trends, similarities and patterns in the activities and movements of the Indian Stock Market in comparison to its international counterparts. This study covered New York Stock Exchange (NYSE), Hong Kong Stock exchange (HSE), Tokyo Stock exchange (TSE), Russian Stock exchange (RSE), Korean Stock exchange (KSE). Data from both Bombay Stock exchange (BSE) and National Stock Exchange (NSE) have been used in the study. The study found Indian markets to be integrated with its global counterparts. Karmakar Madhusudan(2007) investigated the heteroscedastic behaviour of the Indian stock market through market index S&P CNX Nifty for 14.5 years from July 1990 to December 2004 using different GARCH models. First, the standard GARCH approach has been used to investigate whether stock return volatility changes over time and if so, whether it is predictable. Then, the EGARCH models were applied to investigate whether there is asymmetric volatility. Finally, (E) GARCH in the mean extension had been used to examine the relation between market risk and expected return. The study reports an evidence of time varying volatility which exhibits clustering, high persistence and predictability. It is found that the volatility is an asymmetric function of past innovation, rising proportionately more during market decline. It is also evidenced that return is not significantly related to risk.

Khedhiri Sami, Muhammad Naeem (2008) investigated the volatility characteristics of the UAE stock markets measured by fat tail, volatility clustering, and leverage effects, in order to explore a parsimonious model for the UAE stock market and predict its future performance. He used EGAECH, TGARCH and other class of ARCH techniques to model the volatility. Surya Bahadur G.C. (2008) modeled the volatility of the Nepalese stock market using daily returns from July 2003 to Feb 2009 and different classes of estimators and volatility models. The empirical findings did not report any significant asymmetry in the returns and thus suggests GARCH (1,1) model as most appropriate for modeling the heteroskedasticity and volatility clustering in the Nepalese stock market . It also reported high persistence of volatility in the Nepalese stock market. Floros Christos (2008), employed the simple GARCH model, as well as exponential GARCH, threshold GARCH, asymmetric component GARCH, the component GARCH and the power GARCH model using daily data from Egypt (CMA General index) and Israel (TASE-100) index to model the stock market volatility and concluded that increased risk will not necessarily lead to a rise in the returns. The most volatile series has been CMA index from Egypt, because of the uncertainty in prices (and economy) over the period examined

Hojatallah Goudarzi & C.S. Ramanarayanan (2010), examined the volatility of the Indian stock markets and its related stylized facts using ARCH models using data of The BSE500 stock index over a 10 years period. Two commonly used symmetric volatility models, ARCH and GARCH were estimated . The adequacy of selected model was tested using ARCH-LM test and LB statistics. The study concluded that GARCH (1, 1) model explains volatility of the Indian stock markets and its stylized facts including volatility clustering, fat tails and mean reverting satisfactorily. Dana AL-Najjar (2016), estimation and modelled Volatility in Jordan's Stock Market using ARCH/GARCH approach. ARCH, GARCH, and EGARCH have been used to investigate the behavior of stock return volatility for Amman Stock Exchange (ASE) from Jan. 1 2005 through Dec.31 2014. The study found that symmetric ARCH /GARCH models can capture characteristics of ASE, and provide more evidence for both volatility clustering and leptokurtic, whereas EGARCH output reveals no support for the existence of leverage effect in the stock returns at Amman Stock Exchange. Mohammad Naim Azimi (2016), examined the clustering volatility of India's Wholesale Price Index throughout the period 1960 to 2014 by applying the ARCH (1) and GARCH (1) model. The study found no significant effect of previous period's volatility on WPI.

Bodla and Turan (2006) examined the null hypotheses (i) whether the Asian stock markets are co-integrated and (ii) whether there exist the causal relationship amongst the stock prices of select Asian countries. The study has brought out that out of the five Asian stock markets under present study only one (Hong Kong) yielded positive average annual return for both local and the global investors. Further, the Indian stock market shows the highest potential for inclusion in the international portfolio of equity securities as the correlation coefficients of it with other Asian markets are found the lowest. Moreover, there is no co-integration between the Asian equity markets. The Granger causality test, however, brought out that current stock prices in India are influenced by the historical prices of stocks in other Asian countries.

DATA AND PRELIMINARY STATISTICS

To model the volatility of the Indian stock Market, we have used daily closing prices of the most popular stock index i.e. S&P CNX Nifty as proxy to the Indian stock market.

The data ranges for a period of eight years starting from January 2010 to January, 2018. Also, the data range pertains to the post recession period which can provide better inputs about the volatility level in the Indian markets as compared to the world.

Daily closing prices of MSCI- ACWI Index has been used to benchmark the global equity market. The index covers more than 2,400 constituents across 11 sectors and approximately 85 per cent of the free float-adjusted market capitalization as on Sept 2017 in each market across 23 developed and 24 emerging markets.

The data has been collected from yahoofinance.com and has been analyzed using Eviews 7 software.

RESEARCH METHODOLOGY

The present study employs GARCH (1,1) model, EGARCH (1) and Arch-in-Mean model to estimate and compare the level of volatility.

The GARCH specification was given by Bollerslev (1986), formulates the serial dependence of volatility and incorporates the past observations into the future volatility (Bollerslev et al. (1994). *GARCH (1, 1) model can be given by the following formula:*

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

News about volatility from the previous period can be measured as the lag of the squared residual from the mean equation (ARCH term). Also, the estimate of β shows the persistence of volatility to a shock or, alternatively, the impact of old news on volatility.

EGARCH (1, 1):

Proposed by Nelson (1991) & is given by the following equation:

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1 ln(\sigma_{t-1}^2\ ) + \beta_1 \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}}$$

The logarithmic form of the conditional variance implies that the leverage effect is exponential (so the variance is non-negative). The leverage effect is denoted by γ and is present if γ is significantly negative.

RESULTS AND DISCUSSION

Table 1 provides the results of the ADF test and descriptive statistics of the return series have been reported in Table 2. Fig. 1 shows the graphs of the stationary return series. Table 3 reports the result of ARCH LM test and consolidated results of the various GARCH family models used in our analysis have been reported in Table 4.

To make the series stationary, daily logarithmic returns have been calculated from the closing price series as follows:

$$r_t = \log(p_t - p_{t-1})$$

where

r_t = continuously compounded logarithmic return

p_t = daily closing value of index at day t and

p_{t-1} = closing value of index at day t – 1

Thus, the closing value of the index is converted into continuously compounded daily logarithmic return series. Logarithmic returns are calculated since it improves the statistical properties of the data.

The Graph of the MSCI ACSW returns and nifty returns has been shown in Fig. 1 below.

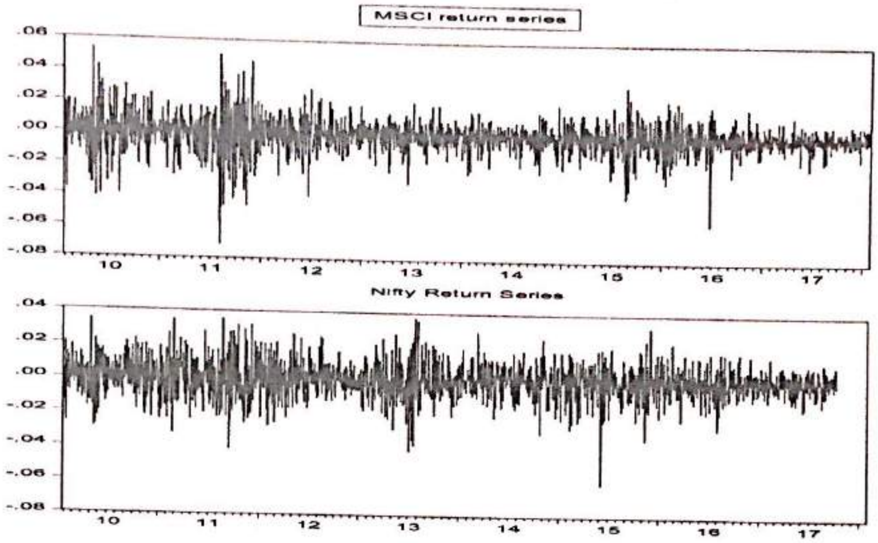

Fig. 1: Graph of MSCI & Nifty Returns

The stationarity of the series has also been confirmed using the Augmented Dickey Test statistic assuming H_0 of non stationarity.

Table 1: The result of the ADF Test is as follows:

	t- statistic ADF test
MSCI ACWI	-46.95065* (0.0001)
Nifty	-41.14387* (0.0000)

*Denotes significance at 5 per cent level.

(P-values have been reported in parentheses)

The probability value of the t statistic is nearly zero for both the return series which calls for rejecting the null hypothesis of unit root and accepting the alternate of stationarity.

The graph of the return series is shown in Fig. 1 above reports constant mean which shows stationarity of the data. The series has a non constant variance, i.e. heteroskedasticity, which is the typical feature of the time series data. Also volatility clustering in the returns can also be easily seen as large changes tend to be followed by large changes and small changes tend to be followed by small changes, which mean that volatility is clustering. Thus the return series shows heteroskedasticity, leptokurtosis & volatility clustering which means linear model will not be able to capture the volatility of the series therefore non linear models such as ARCH/GARCH need to be used for modelling the volatility.

DESCRIPTIVE STATISTICS

Table 2: Descriptive Statistics of MSCI ACWI & Nifty Returns

	MSCI ACWI	*NIFTY*
Mean	0.000313	0.00042
Median	0.000728	0.000493

Maximum	0.053869	0.03738
Minimum	−0.071664	−0.060973
Std. Dev.	0.010264	0.009955
Skewness	−0.513106	−0.193492
Kurtosis	7.87669	4.71576
Jarque-Bera	2084.088	249.9361
Probability	0	0

Table 2 indicates that the returns of MSCI and Nifty are around 0.0313 per cent and 0.04 per cent respectively and with a standard deviation of 1.024 per cent and 0.99 per cent in that order making it evident that Indian markets provide an opportunity of earning more return per unit of risk. Over the time frame considered, i.e. risk per unit of return is lower in the Indian stock market as compared to the world equity market.

The skewness of the returns is negative for both the indices but is higher for the MSCI returns. Thus, there is less probability of earning a negative return in the Indian stock market. The range of the maximum & the minimum return values is also lower in the Indian stock market. The kurtosis of the retuns for both the series is greater than 3, which means that the return series is fat tailed & does not follow a normal distribution which is further confirmed by Jarque Bera Test statistic.

MODELLING THE MEAN

The conditional mean equation has been modeled using Box Jenkins methodology. The correlogram of the series reflects a dynamic pattern suggestive of an ARMA model to be used for MSCI and AR (1) model for nifty series.

ARMA (5, 5) model seems to be the best fit according to the Akaike Information Criterion to capture the dynamics of the MSCI series.

The residuals of the equation when tested using LJUNG BOX Q Statistic showed no correlation but the squared residuals showed high degree of significant correlation. The residuals were further tested for ARCH effects using ARCH LM Test. The F statistic reported by ARCH LM Test (reported in Table 3) is significant and thus rejects the null hypothesis of no heteroskedasticity, necessitating the use of non linear models for capturing the volatility.

Table 3: Result of ARCH LM Test

	MSCI ACWI	*NIFTY*
F statistic	87.79439 (0.0000)	12.27694 (0.0000)

MODELLING THE CONDITIONAL VARIANCE

Since the ARCH LM test confirms the presence of ARCH effects, we use GARCH (1, 1) model to capture the conditional variance of the series. GARCH (1, 1) is the most popular model amongst all GARCH class models.

To capture the asymmetric effects if any, EGARCH (1,1) model has been used. The consolidated results of different models are given in Table 4 below.

Table 4: Result of GARCH(1,1) , EGARCH(1,1)

	Garch (1,1)		*EGARCH (1,1)*	
	MSCI-ASWI	NIFTY	MSCI-ASWI	NIFTY
CONSTANT	1.95E-06 (0.0003)	9.12E-07 (0.0562)	−0.388196 (0.0000)	−0.296514 (0.0000)

ARCH TERM	0.133289 (0.0000)	0.054493 (0.0000)	0.158830 (0.0000)	0.100170 (0.0000)
GARCH TERM	0.852182 (0.0000)	0.936849 (0.0000)	0.972487 (0.0000)	0.976751 (0.0000)
ASSYMETRIC TERM	–	–	−0.138845 (0.0000)	−0.100519 (0.0000)
AIC	−6.661335	6.516270	−6.693117	−6.541820

All the coefficients of the GARCH (1,1) and EGARCH (1,1) equation are highly significant for both the indices. The asymmetric term in the EGARCH model is significant and is negative which indicates the presence of leverage effect, i.e. volatility rises more in response to bad news than good news.

The sum of ARCH term which corresponds to the new news effect is higher and GARCH term which correspond to old news is lower for MSCI index than Nifty which indicates that Indian markets are not informationally efficient as compared to world equity markets. The response of Indian market to new news is much sluggish than that of the global equity market as a whole. The sum of ARCH & GARCH term which shows persistence in volatility is also higher for Indian markets (0.054+ 0.936 = 0.99), i.e. a shock in the present will have a lost lasting effect on the future returns and will die out slowly in around 47 days for global equity market and in approx. 80 days in the Indian stock market. The persistence in volatility has been calculated by using the following formula: $\ln 0.5/\ln(\alpha + \beta)$, Kashifsaleem, (2007).

The results of table 4 indicate that EGARCH (1, 1) model is the better model in estimating the conditional variance of the stock market as per Akaike Criterion as AIC is least for this model.

Now let's take a comparative look at another feature of the return in the stock market.

To capture another feature of the stock market returns, i.e. to know if greater risk allows for greater return, we included variance in the mean equation. The results are as follows:

Table 5: Results for ARCH in MEAN

	ARCH IN MEAN	*ARCH*	*GARCH*
MSCI	−0.183235 (0.9401)	0.133307 (0.0000)	0.852193 (0.0000)
NIFTY	2.316012 (0.6438)	0.057353	0.931968

The risk term incorporated into the mean equation (as GARCH coefficient), is highly insignificant for both the indices, which means that increased risk does not necessarily lead to rise in mean return. i.e. it does not allow for risk premium.

SUMMARY

The returns series in Indian stock market as well as global equity market exhibit characteristics such as volatility clustering , heteroskedasticity and excess peakedness which can be best captured by using non linear models. EGARCH (1, 1) model has been found to be best for modeling the volatility. The study shows that volatility reacts differently to different news. Bad news increase volatility more than good news and asymmetric effect has been found to be higher in Indian stock market and also persistence in volatility is much higher for the same as compared to the global equity market. The long persistence in volatility, lower ARCH term and higher GARCH term indicates that Indian market is informationally inefficient and information is not reflected in stock prices quickly. The result of the ARCH-in-mean model reported that investors taking higher risk are not compensated by high returns in the short run. However, Indian markets have been found to provide more return per unit of risk. This may be due to less effect of global meltdown on Indian markets as compared to others.

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