Empirical Analysis of the Causality between Indian and US Stock Markets' Conditional Volatility: Further Evidence

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Abstract: This paper attempts to investigate the dynamic relationship between the United States (US) and Indian stock markets through the conditional volatility of two stock markets during the 1995-2007 period, using monthly data of BSE-listed BSE 100 and NYSE-listed S&P 500 indices. The research methodology included testing of stationarity with Dickey Fuller test and the use of two-stage GARCH (1,1) model. In the first stage, conditional volatility of both stock markets was estimated, and then it was used as an exogenous variable to estimate further conditional volatility of both stock markets. The study also employed the linear regression model to test the relationship between conditional volatilities of two markets, and finally Granger causality test was used to ascertain the causal relationship between conditional volatilities of two stock markets. The study confirms the interdependency of the Indian stock market and the US stock market by the presence of a strong relationship between conditional volatilities of two markets. The study highlights the interdependency among the stock markets in question and facilitates investor diversification of funds. In fact, in the age of globalisation, integration of stock markets has become a matter of great importance for fund managers and investors as it facilitates to scale down portfolio risk through diversification of funds across the stock markets.

Keywords: BSE 100, S&P 500, conditional volatility, GARCH, causality
JEL classification: C12, C23, C33, C51, N15

1. Introduction

With the opening of capital markets for foreign investors, stock markets are reporting the presence of autocorrelations in stock returns (Sentana and Wadhwani 1992; Faff and Mckenzie 2007). Autocorrelation marks the dynamic linkages between time series data like stock returns, exchange rate, etc., and holds that the trading activities of one stock market considerably affects the investment decisions of investors in another stock market (Rakesh and Dhankar 2009). The existence of such a phenomenon in stock returns exhibits volatile clustering of stock returns and this is referred to as conditional volatility. More precisely, it suggests that large fluctuations in stock returns tend to be followed by large fluctuations, and small fluctuations by small ones. It brings out the fact that present investment decisions are affected by previous trading in domestic and international stock markets. Such particular movements in the stock returns are modeled as conditional volatility wherein volatility of a previous time period is used as an independent variable in estimating the volatility in the current time period. The paper attempts to investigate the dynamic relationship between

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conditional volatility of United States(US) and Indian stock markets. The Indian stock market has witnessed the presence of a large number of foreign institutional investors especially from the US; hence the movements in the Indian stock market depends considerably on the trading activities of the US stock market. Additionally the paper empirically examines how the conditional volatilities between two stock markets are interlinked. In fact, the US has long been the biggest trading partner of India. Table 1 provides statistics on India's exports and imports with reference to the US. India's exports to the US accounts for 17.4 per cent of total exports in the 1995-96 period, rising to 22.8 per cent in the 1999-00 period because of a good economic and trading environment between the two countries. Imports for the same time period, had been 10.5 per cent and 7.2 per cent of total imports. The percentage of total exports declined after the 2002-2003 period because of India's focus on other developing countries.

The hypothesis of the present study is to test that capital flows across the markets affect the trading volume, thereby making the stock markets highly integrated. In modeling the conditional volatility of stock markets, researchers commonly use the autoregressive conditional heteroskedasticity (ARCH) approach. This approach uses conditional variance as a function of past error term and allows the variance of error term to vary over time (Engle 1982). It implies that volatility in the stock market is considerably affected by unexpected variations in stock returns. Bollerslev (1986), further extended the ARCH process by allowing the conditional variance to be a function of past error term as well as the lagged value of conditional variance. This is based on the idea that past error term, which affects current investment decisions and volatility in a previous time period combined, has a significant impact over current investment decisions. Following the introduction of ARCH models by (Engle 1982) and further generalisation by (Bollerslev *et al.* 1992), these models have been extensively used in explaining and modeling the time series data of stock markets.

Table 1. India's trading relation with the US (value in million)

	India's exports to US		India's imports from US		Exchange rate
Year	INR	% share	INR	% share	INR/USD
1995-96	184660	17.4	129160	10.5	33.45
1996-97	232340	19.8	119770	8.8	35.50
1997-98	252820	19.4	188140	9.0	37.16
1998-99	302890	21.7	153140	8.6	42.07
1999-00	363800	22.8	154270	7.2	43.33
2000-01	425100	20.9	137740	6.0	45.68
2001-02	406020	19.4	150210	6.1	47.69
2002-03	527300	20.7	215050	7.2	48.39
2003-04	527980	18.0	231360	6.4	45.95
2004-05	618516	16.9	314581	5.3	44.93
2005-06	761661	17.7	344358	5.4	44.27
2006-07	85395	13.7	57036.6	5.8	42.25
2007-08	83388	12.0	84625	5.9	40.26

Source: Economic Survey of India

2. Literature Review

The present study traces its investigation back to the study of Grubel (1968) to analyse the benefits of international diversification. The progressive deregulation of emerging markets has prompted investors to diversify their funds to reduce the level of risk. If the stock returns between the markets are negatively correlated, then the investor should be able to reduce risk through international diversification. If countries' stock returns are positively co-varying, then it is possible to use the information in one market to predict the movement in another market. For this reason, researchers have made efforts to measure the interrelations across the stock markets. Rao and Naik (1990) applied the cross-spectral analysis and found the relationship of the Indian market with international markets weak, reflecting the institutional fact that the Indian economy has been characterised by heavy controls throughout the entire seventies, with liberalisation measures initiated only in the late eighties. Several studies (Kumar and Mukhopadya 2002; Rakesh and Dhankar 2009; 2010) employed the two stage-GARCH model to study the dynamic relationship across the stock markets using day time and overnight returns. They first extracted the unexpected shocks from the day time returns of one market and used it as a proxy for volatility surprise while modeling the other market's overnight returns in the second stage of modeling. Studies by Eun and Shim (1989), King and Wadhwani (199), Schwert (1990), King *et al.* (199) and Longin and Solnik (1995) reported a time varying relationship and held that stock market returns show high correlation during a period of high volatility. Further, a number of studies (Rao and Naik, 1990; Cheung and Ng 1992; Masih and Masih 2001) employed co-integration and Granger causality test, and held that the US stock market has a dominant role in world stock market integration. Several studies (Huang and Yang 2000; Jong and Roon 2001) examined group stock markets and held there was a strong interdependence across the stock markets. Ewing *et al.* (1999) examined how the North America Foreign Trade Agreement (NAFTA) affected the level of market integration in North America. Their study, however, found no evidence of integration in member markets even after the NAFTA agreement was embedded. Some empirical studies hold monetary variables as dynamic linkages between stock markets. Sasaki *et al.* (1999) and Bracker and Paul (1999) examined the dynamic relationship in accordance with the monetary policies and found significant evidence that monetary variables affect international interdependencies across stock markets. Masih and Masih (1999; 2001) support the common view of the leadership of the US stock market over both the short-term and long-term, and the existence of an important short and long-term relationship between the emerging Asian markets, and the established OECD markets. The study by Arshanapalli and Kulkarni (2001) examined the nature and extent of linkage between the US and the Indian stock markets. The study used the co-integration test to study interdependence between the Bombay Stock Exchange (BSE), and the NYSE and Nasdaq. The results of their study report that the Indian stock market was not interrelated to the US markets for the entire sample period.

The study by Darrat and Zhong (2001), however, produced the opposite results when the markets of the US, Canada, and Mexico were examined. By applying co-integration tests, their results suggest that NAFTA had enhanced the linkages across member stock markets. In conclusion, the majority of studies suggest that market integration has increased significantly over the years. However, a number of studies question this phenomenon and fail to report any dynamic relationship (Cheung and Lee 1993; King *et al.* 1994; Ewing *et al.*

1999). Shamsuddin and Kim (2003) examined integration of the Australian stock market with its primary trading partners, the US and Japan stock markets. The results showed that prior to the Asian crisis, all the three stock markets reported a stable long-run relationship; however, this relationship became weak in the post-Asian crisis period. The results further report that the interdependency between US and Australian stock markets has been reduced while the integration of Japanese and Austrian stock markets remain at a moderate level. A study conducted by Wong *et al*. (2004) investigated the short and long-run dynamic linkages between the Indian stock market and its major trading partners, that is, the US, United Kingdom(UK) and Japan. The study used Granger causality relationship and pair wise multiple and fractional co-integrations. They concluded that the Indian stock market is integrated with mature markets, and is sensitive to the dynamics in these markets in the long run. However, in the short run, both the US and Japan markets seem to have Granger caused the Indian stock market but not vice versa. The study of Yochanan (2006) investigated the dynamic linkages among the BRICs (Brazil, China, India and Russia). The study employed Vector Auto Regression (VAR) models, and concluded that these markets are becoming increasingly more important as the progression of globalisation accelerates. Hoque (2007) conducted an Impulse Response analysis and showed that volatility of the US stock market has a significant impact on the Bangladeshi market. However, the response of the Bangladesh stock market to volatility of the Indian and Japanese stock markets is insignificant.

3. Data and Research Methodology

In this paper, attempts are made to estimate the conditional volatilities of US and Indian stock markets, and thereafter testing of the relationship between conditional volatilities of the two markets. The sample data used in the study consisted of the monthly prices of New York Stock Exchange (NYSE) listed index S & P 500 and Bombay Stock Exchange listed index BSE 100.[1] The data period ranged from January 1995 through December 2007. The S & P 500[2] is a value weighted index and consists of 500 large cap stocks, most of which are American. This index forms part of the broader S & P 1500 and S & P Global 1200[3] stock market indices. All constituent stocks in the index are large public companies that trade on the two largest US stock markets - NYSE and NASDAQ. It represents nearly 75 per cent of the US equities market, and covers 75 per cent market capitalisation. The BSE 100 is also a value weighted index, consisting of frequently traded stocks of all capitalisation categories. The study carries comprehensive analysis which involves estimation of conditional volatility by using GARCH model; and an application of linear regression and vector auto regression

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1 S & P 500 data is downloaded from *www.finance.yahoo.com* and BSE 100 data is from Prowess, a data base maintained by CMIE Ltd.

2 The S & P 1500, commonly known S & P 1500 Composite Index, is a stock market index of US stocks made by Standard & Poor's. It includes all stocks of three indices - S & P 500, S & P 400 and S & P 600.

3 The S&P Global 1200 index is a real time, free-float weighted stock market index of global stocks from Standard & Poor's. The index covers 31 countries and approximately 70 per cent of global market capitalisation. It is comprised of six regional indices- S&P 500 Index, S&P TSX 60 Index (Canada), S&P Latin America 40 Index (Mexico, Brazil, Argentina, Chile), S&P TOPIX 150 Index (Japan), S&P Asia 50 Index (Hong Kong, Korea, Singapore, Taiwan), S&P ASX 50 Index (Australia), and S&P Europe 350 Index.

(Granger causality test) model to study the relationship between stock exchanges. The stock market returns is estimated by applying the natural logarithmic differences. Let P_t be the price of index in time period t, then P_{t-1} will be the price of index in the preceding time period t-1. Thus, the rate of return R_{it} investors will realise in t time period will be

$$R_t = [Log_e (P_t) - Log_e (P_{t-1})]^* 100 \tag{1}$$

3.1 Measurement of Conditional Volatility

The realised return consists of a set of two components - expected return $E(R_t)$ and unexpected return ε_t. Expected return is attributed by stock and economic fundamentals, while unexpected return arises due to good or bad news pertaining to stocks. Symbolically, it can be written as follows:

$$R_t = E(R_t) + \varepsilon_t \tag{2}$$

An upswing in ε_t (unexpected rise in return) suggests arrival of good news; on the contrary, a downswing in ε_t (unexpected decline in return) is a mark of bad news. Volatility in stock market resulting from expected return is marked expected volatility, while volatility resulting from unexpected return is marked unexpected volatility (French *et al.* 1987). Engle (1982) suggests that the conditional variance (σ^2) is a function of the lagged ε' s. It implies that volatility can be forecasted by including past news as a function of conditional variance. This process is called autoregressive conditional heteroskedasticity.

Bollerslev (1986) further generalised the ARCH (q) model to the GARCH (p,q) in which conditional variance depends upon both the squared residuals and its own lagged value, which symbolically can be written as follows:

$$\sigma^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \tag{3}$$

A large number of studies advocate the use of GARCH (1,1) and hold that it is sufficient to capture volatility in time series data (Bollerslev *et al.* 1992; Aggarwal *et al.* 1999; Dhankar and Chakraborty 2007). The present study also used GARCH (1,1) to estimate the heteroskedasticity effect on US and Indian stock market volatility in the first stage by estimation of Equation 3. The second stage involved the estimation of Equation 4 for Indian stock market volatility wherein conditional volatility of S & P 500 was used as the independent variance regressor for measuring the conditional volatility of BSE 100, and likewise for measuring the conditional volatility of S & P 500, BSE 100 was used as the independent regressor, as shown in Equation 5.

$$\sigma_{BSE\,100}^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \alpha_3 \sigma_{t(S\&P\,500)}^2 \tag{4}$$

$$\sigma_{S\&P\,500}^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \alpha_3 \sigma_{t(BSE\,100)}^2 \tag{5}$$

4. Empirical Findings

4.1 Preliminary Results

To provide a general understanding of US and Indian stock markets, Table 2 outlines the basic statistics of S & P 500 and BSE 100 returns. The average returns of both indices were positive, highlighting the fact that stock indices have increased over the period of time. The

Table 2. Descriptive statistics of Indian and US stock markets

Statistics	BSE 100	S & P 500
Mean	1.159	0.756
Median	2.094	1.204
Maximum	16.993	9.232
Minimum	-23.494	-15.758
Std. Dev.	7.902	4.126
Skewness	-0.432	-0.782
Kurtosis	2.917	4.251
J-B Statistics	4.904*	26.101*
	(0.018)	(0.000)

Note: * significant at 5% level; ρ value in parentheses.

negative skewness of both stock market returns indicates that returns are negatively skewed. The negative skewness indicates that the markets have a higher probability of providing negative returns. The high values of kurtosis of S & P 500 exhibit that S & P 500 return has a heavier tail than the standard normal distribution; however, it is low in case of BSE 100 return. The Jarque-Bera test which examines the normality of return is significant at 5 per cent level for both the indices. It shows that returns are not normally distributed in US and Indian stock markets.

4.2 Unit Root Test

Table 3 examines the unit root presence in the returns of both the stock markets. The Augmented Dickey Fuller test was used to measure the stationarity property of the US and Indian stock markets series of returns. The test rejected the null hypothesis of unit root presence and held stationarity in time series. The presence of stationarity highlights that current stock returns are significantly affected by previous stock returns.

4.3 Forecasting of Conditional Volatility in US and Indian Stock Markets

Figures 1 and 2 measure the returns clustering of monthly returns of BSE 100 and S & P 500 respectively. A careful examination of the index movements highlights volatility clustering. Once volatility clustering was traced, the study used the vanilla GARCH (1,1) model in the return series for both the stock markets. While running the GARCH (1,1) in the mean process, coefficients of the model with their standard error and 'z' statistics were estimated (Table 4). The ARCH (1) coefficient α_1 for Indian stock market is reported to be significant

Table 3. Unit Root Test (ADF Test) of Indian and US stock markets

	BSE 100	S & P 500
Constant	-5.499*	-5.077*
	(-3.475)	(-3.474)
Constant with Trend	-5.926*	-5.247*
	(-4.02)	(-4.021)

Note: * Significant at 5% level. Mackinnon critical values for rejection of hypothesis of a unit root in parentheses.

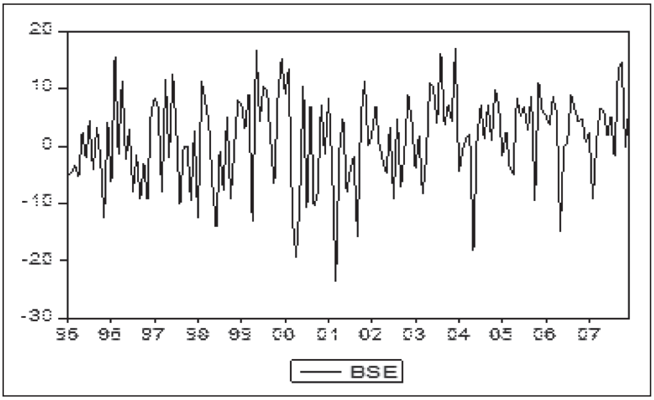

Figure 1. Returns clustering of BSE 100

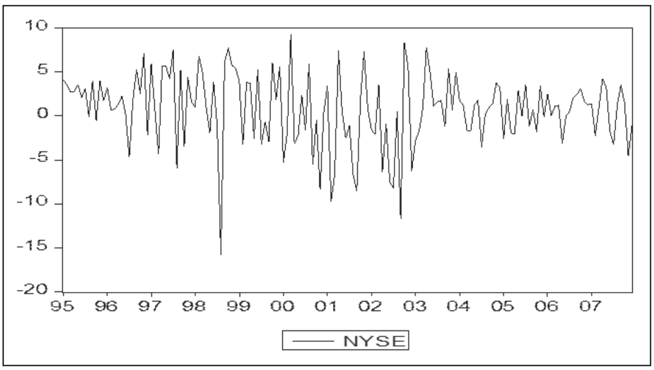

Figure 2. Returns clustering of S & P 500

Table 4. Fitting of GARCH (1,1) in mean model in BSE 100 and S & P 500 stock markets

Stock market	AR(1)	Constant α_0	ARCH(1) α_1	GARCH(1) α_2	Var. regressor α_3
BSE 100	1.197*	51.59*	-0.157*	-0.215	1.835*
	(90.023)	(0.058)	(0.000)	(0.703)	(0.001)
S & P 500	0.897*	1.758	0.125	0.859*	-0.021
	(0.000)	(0.872)	(0.127)	(0.000)	(0.899)

Note: * Significant at 5% level of significance; ρ value in parentheses.

at 5 per cent. What this means is that good or bad news which is measured by the lagged error term has a significant impact upon current volatility. However, in case of the US stock market, it is not significant, indicating that past good or bad news has no impact upon current volatility. These findings question the efficient market hypothesis in the Indian context, where current investment decisions are significantly influenced by last decisions

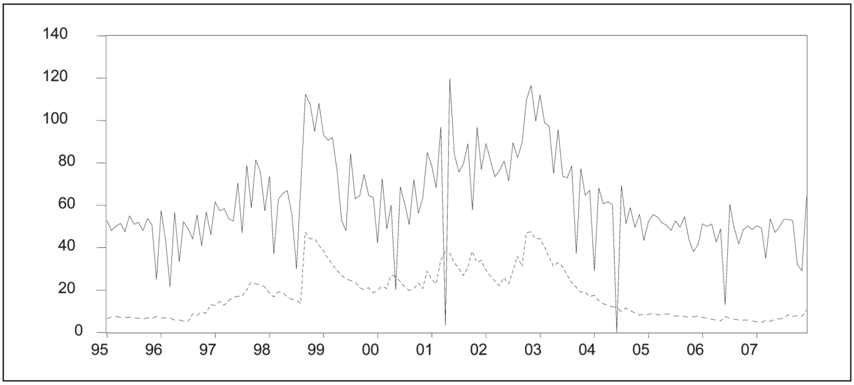

Figure 3. Conditional volatility in BSE 100 and S & P 500

of investors. The GARCH (1) coefficients α_2, which signifies the relationship between previous time volatility and current volatility, is significant for the US stock market; however, it is not significant for the Indian stock market. The variance regressor, for BSE 100 is significant, indicating that volatility in the US stock market has significant bearings on the volatility of the Indian stock market. However, it is not significant in the case of S & P 500, indicating that volatility in the Indian stock market has no influence on US stock market volatility. Figure 3 shows the time series plot for estimated series of conditional variance for BSE 100 and S & P 500 respectively. Conditional volatility as depicted in the figures moves qualitatively with the apparent volatility variations in the returns as indicated in Figures 1 and 2. From Figure 3, months with the highest volatility can be traced with reasons why the market showed high conditional heteroscedasticity during those periods. A careful examination reports that the high volatility periods in both stock markets coincide. Recent empirical studies indicate that the impact of good or bad news is asymmetric on volatility (Nelson 1991; Chiang and Doong 2001). That is, good and bad news has a different magnitude of impact on investment decisions.

4.4. Testing the Relationship between Conditional Volatilities of Two Markets

In this section, the study employed the simple linear regression model to estimate the relationship between conditional volatilities of two markets. Equation 6 was used to estimate the relationship as shown below:

$$\boldsymbol{\sigma}^2_{t(BSE100)} = \boldsymbol{\phi}_0 + \boldsymbol{\phi}_1 \boldsymbol{\sigma}^2_{t(S\&P500)} \tag{6}$$

Here, the study tested the null hypothesis that conditional volatility of two markets is not significantly related, that is, $H0 : \phi_1 = 0$. It was tested against the alternative hypothesis, that conditional volatility of two markets is significantly related, that is, $H1 : \phi_1 \neq 0$. Table 5 shows that the value of slope ϕ_1 is significant at the 5 per cent level, indicating that volatility in the Indian stock market is significantly affected by volatility in the US stock market. The value of R-Square indicates that 56 per cent variations in the Indian stock market volatility is explained by volatility in the US stock market. These results just report the relationship; however, we have no means to ascertain the causal relationship between the conditional volatilities of two markets.

Table 5. Linear regression results

Dependent Variables	Constant ϕ_0	Slope ϕ_1	R-Square
$\sigma^2_{t(BSE100)}$	36.753* (0.000)	1.387* (0.000)	0.56

Note: * Significant at 5% level of significance; ρ value in parentheses.

4.5 Granger Causality Test

The high correlation between conditional volatility of S & P 500 and BSE 100 is in no way indicative of causation. To find the cause and effect relationship, the study further used the Granger causality test which is based on VAR with adequate lags length that correspond to reasonable beliefs about the longest time over which one of the variables could help predict the other. The test examined whether past changes in one stationary variable facilitate to forecast current changes in another stationary variable. To test for Granger causality from the S & P 500 to BSE 100, and BSE 100 to S & P 500, a bivariate VAR model with one lag was estimated for all pairs of BSE 100 and S & P 500 conditional variance, as depicted in Equations 7 and 8. The study tested the null hypothesis ($H0 : \lambda_i = 0$) against the alternative hypothesis ($H1 : \lambda_i \neq 0$). The significance of F statistics called for the rejection of null hypothesis against the alternative hypothesis. The conclusion drawn is that S & P 500 Granger causes BSE 100 volatility; however, rejection of the alternative hypothesis leads to the acceptance of null hypothesis that BSE 100 does not Granger cause S & P 500 volatility respectively (Table 6).

$$\sigma^2_{t(BSE100)} = \lambda_0 + \lambda_1\sigma^2_{t-1(BSE100)} + .\lambda_2\sigma^2_{t-1(S\&P500)} \tag{7}$$

$$\sigma^2_{t(S\&P500)} = \lambda_0 + \lambda_1\sigma^2_{t-1(S\&P500)} + \lambda_2\sigma^2_{t-1(BSE100)} \tag{8}$$

Table 6. Granger causality test results

Null hypothesis	F-statistics	Probability
S & P 500 volatility does not Granger cause of BSE 100 volatility	112.375*	0.004
BSE 100 volatility does not Granger cause of S & P 500 volatility	2.521	0.113

Note: * Significant at 5% level.

5. Conclusions and Implications of the Study

The study examined the issue of growing interdependency of financial markets in the context of globalisation. The empirical results reveal the dynamic co-integration relationship in the volatility of US and Indian stock markets. Both the stock markets have reciprocal influence on volatilities due to large fund flows from one market to another. In the study, the independent regressor was used to estimate the dynamic influence on conditional volatility of BSE 100 in the case of NYSE volatility and of S & P 500 conditional volatility in the case of BSE volatility. The GARCH (1,1) results (Table 4) report that the variance regressor is significant in the case of BSE 100, indicating that ups and downs in the US stock market influence the Indian stock market. The regression results (Table 5) suggest a significant relationship in the volatility between the two stock markets. To find out the casual relationship, the study further used the Granger causality test which reports that volatility of the BSE is not a cause of the NYSE volatility, but NYSE volatility is significantly a cause of BSE volatility.

The research highlights that liberalisation of financial systems is promoting the flow of funds from one market to another resulting in strengthening interdependency of stock markets. The empirical findings of the present study should facilitate investors in working out investment strategies and diversification of funds to reduce potfolio risks.

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