



INVESTMENT OPPORTUNITIES IN INDIAN AND CHINESE STOCK MARKETS

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Abstract

The association among risk and return is crucial within finance theory; this study done considering return in three angles, asymmetric condition of stock market in India and China from 01.01.1995 to 31.12.2016. Due to the financial crisis in 2008 the data split into pre and post crisis using EGARCH –M and HL calculator. Indian market proved leverage effect, whereas Chinese market showed different leverage patterns. Trade-off between risk and return varies in different market state, conditional volatility persisted for more days in Chinese market than Indian and Chinese market is more volatility persistent with positive shocks which disproved asymmetric theory.

Key words: Asymmetric, risk-return, volatility, stock market, E-GARCH, GFC – Global financial Crisis

I. INTRODUCTION

Risk and return are crucial phenomenon in investment management. Risk, lead to a prospect of losing a part or yet the entire investment. “Return,” on other side, is the gains (or losses) from an investment. If the risk is low then the, probable returns tend to be low, and high level of risk are normally related to high possible returns. It is also important to understand that higher risk does not always equals to greater return, tradeoff between risk and return only indicates that high risk levels are allied with the option of high returns, moreover losses on an investment also incurred with higher risk. Financial viability and risk bearing capacity of an investors will determine the type of investment to be chosen.

Leverage effect is synonymous with asymmetric volatility in which response of the asymmetric nature of the volatility to return shocks replicate the subsistence of time-varying risk premiums. ((Pindyck (1984), French, schwert, and Stambaugh, (1987)). In asymmetric market there will be a negative correlation between stock return volatility and stock return which is popularly called as leverage theory resulting the fall in stock value as a result there will be a financial leverage and thereby the stock become more riskier.

Risk is the probability of loss and volatility implies the fluctuations in the price of an investments over its entire life. Standard deviation and beta are the two measures of absolute and relative volatility respectively. Investors who are risk averse will go for investment with low volatility and risk lovers will be able to bear the violent fluctuations in the price of their investment. In asymmetric return the nature of volatility is conditional, unlike the common volatility. The conditional volatility provides information each day i.e., "tomorrow's volatility estimate depends on (is conditional on) certain new information. The conditional volatility is assumed to be persistent when return at present has a significant consequence on the future variance. This means that if the unconditional variance tends to infinity, it is assumed as if the volatility is persistent.

Many researchers have studied stock market volatility across the globe specifically taking developed markets; the relationship between the equity variance with various explanatory variables had been studied by Christie (1982), and reported that there is a positive association between financial leverage and the equity variances which is contrary to the forecast of the options literature and interest rates. The correlation between market risk premium and volatility of stock returns was studied by French et al (1987) and found the relationship to be positive. The temporal behavior of market returns was also analysed by the researchers and found that conditional variances are found to be high accuracy. [(Akgiray (1989)]. In another perspective few authors examined Heteroskedasticity in Asset returns and reported that the ARCH effects disappear when volume is incorporated in the variance equation. [Lamoureux et al (1990), Nelson (1991)]

Volatility has been analysed differently by different authors. The yield curve and the time-varying conditional volatility link was checked by Engle and Ng (1991) and demonstrated different shaped yield curves and various combinations of volatility on future spot rates. Researchers have also made more imminent into the relationship between volatility and the return of industrialized countries, applying GARCH-M model. [Theodossiou and Lee (1995), Mougoni and White (1996), Franses and Van Dijk (1996), Jorge Caiado (2004), Duffee (2005)].

The present study focused on Indian and Chinese stock markets since India and China. The empirical literature for the Indian and Chinese stock markets is still limited to only a few comprehensive studies such as Song, Liu and Romilly (1998), who studied Chinese aggregate consumption function by applying TVP (time varying parameter) method and found that TVP outperforms other models and it is found to be a good representation of the changes in Chinese consumer behaviour over time. In another study by Cheng Xu (2000) used autoregressive models to characterize the time series of Shanghai stock returns, and found to be a high volatile market. The study also reported that in many aspects foreign shares perform differently from domestic shares. Robet Brooks & Vanitha (2003) investigated the existence of autocorrelation cross correlation among four main stock markets of India and China. The study found spill-overs from Shenzhen 'A' prices to 'B' shares prices also there is no volatility spill-over from 'B' to 'A' share prices. Indian stock market volatility has been studied by Harvinder kaur (2004) considering Nifty and BSE indices and found there is volatility persistent and the indices are responding to the arrival of asymmetric news.

Chinese market operation and efficiency had been studied by Seddighi and Nian (2004) and found that Chinese market is not following random-walk process as expected in the Market Efficiency Theory. However, Hongyu pna and Zhichao Zhang (2006) reported that the random walk method as the worst performing method. Niu, H., & Wang, J. (2013) studied dynamics of nonlinear analysis of Chinese stock market indices such as Shanghai and Shenzhen composites. Ning, and Xu, and Wirjanto (2015) applied copula-based univariate time series model and analysed volatility clustering of asset returns and found strong nonlinear and asymmetric volatility in the returns.

There are good number of studies on Indian and Chinese Stock Market like development of stock market, effect of macroeconomic factors on stock market development and so on however only a few studies concentrated on risk return trade off and stock market volatility applying symmetric models.

Since the volatility feedback increase large negative stock return and making stock returns negatively skewed, the asymmetric model better fits the data than the other standard GARCH family models. Thus the present study adopted asymmetric model to measure the risk return trade off and the persistence of conditional volatility and examined the return in three angles, the leverage effect phenomenon, risk return trade-off and the mechanism of conditional volatility applying asymmetric model.

II. DATA & METHODOLOGY

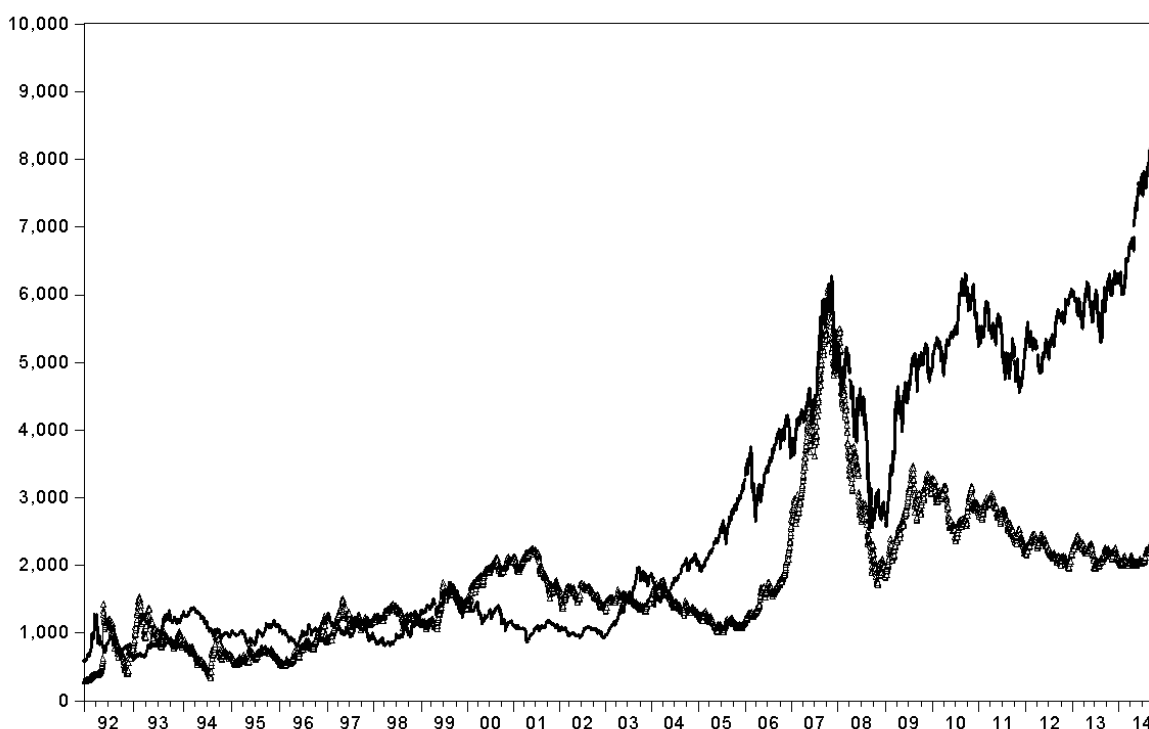
Data considered for this study are daily closing indices of Nifty 50 (India) and Shanghai Composite Index (China) for the period from 01/01/1995 to 31/12/2016. For the purpose of analysis prices were converted in to return by taking the difference of indexes and log of such first difference. Stationary properties of the variables are checked through structural break Unit Root Test, ADF and PP test statistics. The EGARCH-M Model is used to identify the patterns of the asymmetric volatility of market return and the risk-return trade-off during different study periods. Volatility persistence is measured by way of volatility Half-Life calculator.

III. LONG TERM MOVEMENTS OF MARKETS

The basic trend line of any financial time series emphasizes the propensity of data to grow or decline over a period of time. Trend line graph explains the long term movement of the series without seasonal and cyclical or business factors. The figure presented below shows long term movement of the Indian and Chinese stock markets over the study period from 1995 to 2016.

The graph shows an upward trend till the end of 2007 and there is a sudden drop and it picked up during the beginning of 2009; which revealed data breakup in the series at the end of 2007 due to the subprime Crisis, thus the study considered the structural break the data split into pre and post global financial crisis and separate analysis done for all the periods, to determine the robustness.

Trend line of Indian and Chinese Stock Markets



The descriptive statistics (Table 1) shows the normality and characteristics of a time series. It is found that Shanghai Composite Index has higher mean in the pre-crisis and lower in its post-crisis period whereas Nifty reported a same mean value for pre and post-crisis periods. The low mean and variance generally show low expected returns and risk. Shanghai composite return is more volatile in the pre-crisis period, than Nifty, and in other periods it has recorded comparatively high volatility. The higher volatility cause higher rate of returns but involves more risk. The return series for markets during pre-crisis period show negative skewness for nifty and positive skewness for Shanghai Composite and it is contradicting in the post-crisis period as Nifty is positively skewed whereas Shanghai is of negative value. The negative skewness suggests that the distribution has long left tail (lower values), meaning that negative stock returns are found to be more common than positive returns. Whereas the positive skewness suggests an asymmetrical distribution with a long tail to the right (higher values) indicating that positive returns are more common and also there is a probability of a large increase in return. The standard value of kurtosis of 3.0, as per to Gaussian distribution and any excess values (that is >3) indicates fat tails kind i.e., the return has heavier tails than normal distribution and the probability of positive and negative return is high. The Jarque-Bera (JB) test of normality proved that the series are non-normal in all cases, which can be expected in stock market data since it exhibits asymmetry, thus it can be built-in with non linear models.

Table 1: Descriptive statistics of the returns

	CNX Nifty			Shanghai Composite		
	Whole period	Pre crisis	Post crisis	Whole period	Pre crisis	Post crisis
Mean	0.0005	0.0006	0.0006	0.0004	0.0007	0.0003
Median	0.0008	0.0009	0.0005	0.0005	0.0005	0.0008
Maximum	0.1633	0.1209	0.1633	0.7756	0.7192	0.0594
Minimum	-0.1305	-0.1305	-0.0610	-0.1791	-0.1791	-0.0887
Std. Dev.	0.0166	0.0172	0.0122	0.0247	0.0271	0.0155
Skewness	-0.1375	-0.2460	1.2768	6.0934	5.7359	-0.7615
Kurtosis	10.2885	2.8685	2.6734	18.6581	4.1874	3.2008
Jarque-Bera	12900*	5626*	27631*	76898*	31496*	1402*
Observation	5820	3893	1685	5820	3893	1685

IV. UNIT ROOT TEST

The stationarity tests of the series were investigated through Structural break unit root test, ADF and PP test presented in Table 2, 3 & 4. The top section of this output shows, break specification, and the break type. The study applied the Unit Root Test with Break Point¹ for whole period to position the endogenic structural break; the test shows as break points lying during November 29, 2007 (Nifty 50) & 14 November 2007 (Shanghai Composite Index). Therefore the study accounted Global Financial Crisis and analysis was done separately for three periods such as whole period, pre and post crisis, in order to consider the GFC (Salvador 2012, Salvador et al 2014)². Therefore in post crisis period, observations of crisis period are not included, and in addition, structural break is incorporated for the whole period by setting dummy variables by taking a value of one from structural break points and zero elsewhere. The second section reports the Augmented Dickey-Fuller t-statistic for the Unit Root test, along with Vogelsang's asymptotic P-values. The test resulted in a statistic of -34.0071 (Nifty 50) & -29.0216 (Shanghai Composite), (with 0.01 P-value), leading to null hypothesis rejection. (Table 2). Stationarity was checked by ADF and PP tests for Pre and Post crisis Period separately. Both the test (PP and ADF) statistic rejected the null hypothesis that "there is no unit root in the series" (at 1% los) for all periods. This ensures that time series stochastic models can be used for further empirical analysis.

Results of Unit Root with Break Test (Whole Period)

Table 2. Break Selection: Minimize Dickey-Fuller t-statistic

(Automatic - based on Schwarz information criterion)

	CNX Nifty		Shanghai Composite Index	
Break Date	11/29/2007		11/14/2007	
	t-Statistic	Prob.*	t-Statistic	Prob.*
ADF-test statistic	-34.0071	< 0.01	-29.0216	< 0.01
Critical values:				
1% level	-4.949133		-5.347598	
5% level	-4.443649		-4.859812	
10% level	-4.193627		-4.607324	

¹ Perron, Pierre. "Further evidence on breaking trend functions in macroeconomic variables." *Journal of econometrics* 80.2 (1997): 355-385.

² The evidence of a risk return trade off would be unclear if the financial crisis period is included. Salvador, E. (2012). The risk-return trade-off in emerging markets. *Emerging Markets Finance and Trade*, 48(6), 106-128.

* The top section of this output describes the break specification displays the selected break date and lower section reports the Augmented Dickey-Fuller t-statistic for the unit root test.

Unit Root test for Pre and post crisis period

Results of ADF and PP test (for pre and post crisis period)

Table 3 ADF unit root test for the stock return series based on SIC at level.

Return series at level based on SIC, (max lag=1)

	CNX Nifty		Shanghai	
	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis
ADF-test statistic	-34.21579*	-38.83726*	-59.4344*	-7.75666*
Critical values:				
1% level	-3.431846*	-3.434029*	-3.43185*	-3.43403*
5% level	-2.862086*	-2.863052*	-2.86209*	-2.86305*
10% level	-2.567104*	-2.567622*	-2.5671*	-2.56762*

Table 4 PP unit root test for the stock return series based on SIC at level.

Return series at level based on SIC, (max lag=1)

	CNX Nifty		Shanghai	
	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis
ADF-test statistic	-55.69975*	-38.78522*	-59.7765*	-10.2701*
Critical values:				
1% level	-3.431845*	-3.434029*	-3.43185*	-3.43403*
5% level	-2.862086*	-2.863052*	-2.86209*	-2.86305*
10% level	-2.567104*	-2.567622*	-2.5671*	-2.56762*

V. ARCH EFFECT IN RESIDUALS

Existence of ARCH effects in the residuals is one important aspect which is necessary to ascertain before applying GARCH models, which tests whether the variance of the residuals varies widely or constant over time. If it is constant over time then regression model would provide a good explanation to the series however the basic assumption of the linear structural model is that the variance of the errors is constant over time and that cannot be considered for stock market data as they exhibit time-varying heteroskedasticity. If the results prove heteroskedasticity then it gives assurance to apply advanced GARCH models and their extensions. The test results shown in Table 5, clearly rejects the null hypothesis (as LM test statistic is statistically significant and > critical value in chi square), to infer that there is ARCH effect in the series, therefore advanced non-linear model can be applied for further analysis.

Table 5: ARCH-LM test for residuals of returns series

	CNX Nifty			Shanghai Composite		
	Whole Period	Pre-Crisis	Post-Crisis	Whole Period	Pre-Crisis	Post-Crisis
ARCH-LM test statistic (n*R2)	412.9309	464.642	33.9685	1.9525	18.3140	820.307
Prob. Chi-square	[0.000]*	[0.000]*	[0.000]*	[0.025]*	[0.019]*	[0.000]*
F-statistic	385.6980	527.362	2.8669	23.388	2.29477	1597.51
Prob. (F-statistic)	[0.000]*	[0.000]*	[0.000]*	[0.024]*	[0.018]*	[0.000]*

Notes:*Significant at the 1% level. Figures in [.] refer to p- values. The LM version of the test statistic is defined as n*R2 (where n is the number of observations and R2 is the coefficient of correlation).

Ho: There is 'no ARCH effect' in the series or series are homogeneous

VI. THE RISK-RETURN TRADE-OFF UNDER E-GARCH SPECIFICATION.

This section focuses on measuring the asymmetric volatility and the risk-return trade-off in the Indian and Chinese markets. A number of studies argue that there is no major difference in the results of including and excluding the risk-free rate when examining the risk-return trade-off³. A general statistical model was developed by Merton (1973) to test the relationship between returns and its volatility, excluding the risk-free rate, the formula is in below format.

$$E(R_{it}) = \omega + \psi \sigma_t^2(R_{it}) \quad \text{----- (1)}$$

³ Nelson (1991), Li et al.(2005) and Salvador et al (2014)

Where R_{it} is the asset return, i at time t , ω is a constant, σ_t^2 is the asset variance and ψ is the coefficient of the risk aversion

The coefficient of risk aversion should be positive and significant, as investors require a higher premium when the assets become riskier. But this model does not observe the conditional variance. However literature provides some econometric techniques to overcome the limitations of the Model. One of the notable techniques is GARCH in Mean Model. In GARCH model, the conditional variance is part of the mean equation directly, and the return of a security may depend on its volatility and hence a simple GARCH-M (1, 1) model can be written as:

$$\text{Mean equation: } r_t = \mu + \lambda \sigma_t^2 + \varepsilon_t \quad \dots\dots\dots (2)$$

$$\text{Variance equation: } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad \dots\dots\dots (3)$$

Here, coefficient, λ , captures changing risk premium and its dynamic pattern over time and is interpreted as the trade-off between excess returns and the conditional variance. A positive λ indicates that the return is positively related to its volatility, i. e. a rise in mean return is caused by an increase in conditional variance as a proxy for increased risk. The GARCH –M model is a popular model however it is symmetric. Since the stock returns are asymmetric in nature, the researcher considers this fact in the empirical approach so as to treat the impact of negative and positive shocks differently. The variant on GARCH to account for the asymmetry between up and down moves is the Exponential GARCH model of Nelson (1991). The presence of leverage effect can be tested, and the model uses the logarithm of σ_t^2 which makes the conditional variance regardless of the signs of co-efficient in the results.

The conditional variance can be specified as

$$\log \sigma_t^2 = \omega + \alpha_1 \left\{ \frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \frac{\sqrt{2}}{\pi} \right\} + \beta \log \sigma_t^2 + \gamma \left[\frac{\varepsilon_{t-1}^2}{\sigma_{t-1}^2} \right] \dots\dots\dots (4)$$

(Where, ψ - Risk aversion, ω - constant, α - Arch effect, γ - leverage effect, β - Garch effect)

The presence of leverage effect can be detected with the hypothesis $Y < 0$ and if its $Y > 0$ the impact is asymmetric. The impact is symmetric if $Y=0$. Thus, there is leveraging impact which states that the volatility will be higher after negative shocks.

In order to capture the risk return trade off in asymmetric condition, the study uses the Hybrid model called i.e. E-GARCH – M model.

The phenomenon of volatility clustering implies that volatility shocks today will influence the expectation of volatility many periods in the future. Such fact is known as volatility persistence. The forecast of the future volatility will depend upon information included today's information set (e.g. today's returns). Volatility is said to be persistence if today's returns has a large effect on the forecast variance many periods in the future.

A measure of the persistence of volatility is the "Half-Life" of volatility. It can be defined as the time taken for the volatility to move halfway back towards its unconditional mean following a deviation from it, which can be calculated by $HL = \ln(0.50)/\ln \theta_2$.

VII. EMPIRICAL ANALYSIS AND DISCUSSION

The results are presented in Table 6.

Results for whole study period (from 1995 to 2016)

It is observed in the mean equation, that the risk aversion parameter ψ of the Indian market is negative and insignificant, whereas the leverage coefficient γ is negative and significant; this indicates negative shocks have a significant role in the absence of risk-return trade-off in during the period. But the Chinese market reported positive and significant risk premium parameter λ , i.e., there is a positive trade-off between excess returns and the conditional variance is and the return and volatility are positively related, i.e. a rise in mean return is caused by an increase in conditional variance as a proxy for increased risk. This suggests that in the midst of negative shocks, there is evidence of positive risk-return trade off in Chinese Stock Market.

The evidence of asymmetry in the whole period for both markets indicates that negative news is responsible for the higher volatility than the positive news. In other words, bad news causes the market to react more favorably, i.e. causing volatility to rise and to increase investors' confidence with the higher expected return.

The daily parameters shown in the table such as GARCH reaction parameter α and persistence parameter β lie within the normal ranges (0.85 and 0.98) as the unconditional betas are close to 1 for the leveraged stocks. It also shows high persistence and low reaction for both the markets.

H-L of volatility is used to measure the persistence of conditional volatility. Results show that Shanghai takes comparatively more time to return back to its unconditional mean. The impact of volatility lasts for 20 days (approx.). For Nifty the impact of volatility lasts for 13 days (approx.).

Considering the structural break in the data series due to GFC the analysis separately for pre and the post-crisis done and the results are presented in table 6.

Results for Pre-crisis Results (from January 1995 to November 2007)

The table shows that risk aversion parameter ψ for Nifty and Shanghai is positive and significant; the leverage coefficient γ for both the market is negative and significant. This indicates that the episodes of negative news play a significant role than the positive or good news.

Positive and significant risk aversion parameter with negatively significant leverage coefficient suggests some evidence of positive risk-return trade off in asymmetric effect for pre-crisis period.

The trade-off between excess returns and the conditional variance for both the market is positive in pre-crisis period as expected. The daily parameters shown in the table such as GARCH reaction parameter α and persistence parameter β lie within the normal ranges and unconditional betas are close to 1 for the leveraged stocks. It also shows high persistence and low reaction for both the markets.

The forecast of the future volatility will depend upon information included today's information set (e.g. today's returns). Volatility is said to be persistence if today's returns has a large effect on the forecast variance many periods in the future. The half-life volatility persistence provides a quantified approach in terms of exact days required for volatility to come back to its average.

In the pre-crisis period, Chinese Market takes more time to return back to its unconditional mean than Indian market, as the impact of volatility lasts for 25 days (approx.) for Shanghai which is more when compared to the Nifty, in which impact of volatility lasts for only 6 days (approx.).

Results for Post-crisis period (from March 2009 to December 2016)

The post-crisis result reported that in Chinese market there are evidences of risk return trade off (ψ is positively significant), with no asymmetric effect, whereas for post crisis there is an evidence of negative trade-off in asymmetric market condition. (Negatively significant @ 10% level), which means the return is negatively related to its volatility, i. e. a rise in mean return resulted decrease in conditional variance and decline in risk, which can be the effect of GFC.

There is a strong evidence of reverse asymmetry in Chinese market (positive leverage coefficient γ) i.e., positive return causes market to react more favorably, causing volatility to rise and to increase investors' confidence with higher expected return. It can also be inferred that the good news is responsible for the higher volatility and negative shocks had less impact on the conditional variance.

The daily parameters (GARCH reaction parameter α and persistence parameter β) for the post-crisis period also lie within the normal ranges and unconditional betas are close to 1 for the leveraged stocks. It also shows high persistence and low reaction for both the markets. Whereas the Chinese market in post crisis reveals that leverage effect has no influence in conditional beta, as there is evidence of positive leverage with raise in persistent parameter, which is inconsistent with leverage theory.

It is also evident that negative shocks increase the risk premium much more than the positive shocks.

However one notable outcome that can be obtained by HL test is that the persistence of volatility for an index with positive shocks (positive γ coefficient) is more than that of negative shocks. As HL test results show Shanghai Composite with positive return takes more time to return back to its unconditional mean i.e., the impact of volatility lasts for 99 days (approx.). But for nifty, with leverage effect the impact of volatility lasts only for 25 days (approx.).

VIII. FINDINGS

The results of the leverage effect show that Indian market since market is asymmetry for all the three study periods, and as a result leverage phenomenon is proved. But Chinese markets during the post-crisis period resulted contrary to the theory and found reverse asymmetry however leverage theory is proved for the rest of the periods. In addition to that, the reaction (ARCH) and persistence (GARCH) parameter for both market returns are lie within the normal ranges. It was also found that Risk-Return trade off for the Indian market is evidenced only in the pre-crisis period whereas for Chinese market it is evidenced for all the three study periods, irrespective of leverage effect. It was also noted that negative return shocks increase the risk premium much more than the positive shocks. The conditional volatility persisted more days in Chinese market than Indian and volatility persisted for long days in the non-asymmetric market than the asymmetric market. (E.g. Shanghai CI with positive returns takes more time (99 days) to return back to its mean than the periods showing leverage effect). In addition, Shanghai Composite taking more time to return back to its mean with long lasting impact evidenced in positive shocks, leading to reject the theoretical mechanism behind the asymmetry which says negative shocks increase conditional volatility substantially.

IX. CONCLUSION

The study investigated the leverage effect and the time-varying risk premium and the asymmetric volatility phenomenon of Indian and Chinese Market. The mechanism behind the asymmetry is that negative shocks increase conditional volatility substantially. The study examines the nature of volatility and the risk-return trade-off in the Indian and Chinese stock market, and to see results more clearly, the separate analysis conducted accounting GFC. (pre-crisis, post-crisis and the whole period). The results provide some evidence of different patterns of volatility and the risk-return relationship due to the different state of market performance. The peak in the volatility typically corresponds to large declines in the market, i.e., the stock return volatility tend to rise leverage, this phenomenon, is called as predictive asymmetric⁴. Given this evidence there is a reason to expect such effect to exist in conditional betas as well. However, it is found that leverage effect on volatility seems small compared to the symmetry generated through the shocks in GARCH specification. Yet, the result reveals that negative shocks have more impact than positive shocks Indian market irrespective of accounting GFC. Whereas the Chinese market in post crisis reveals that leverage effect has no influence in conditional beta, as there is evidence of positive leverage with raise in persistent parameter, which is inconsistent with leverage theory.

X. IMPLICATIONS

Chinese market (Shanghai Composite) is high volatile among these two markets, and the risk-seeking investors can earn several times their investment. Investors seeking a high rate of return can invest in Chinese market; the results also indicates that whether market is levered or not, risk premium is assured in Chinese Market, investment in Indian market is risky relatively when big events like Global Financial Crisis takes place stock market is tend to react and therefore risk lovers have to be careful as there is a possibility for losing risk premiums. However the positive part is that Indian market is relatively low volatility persistent compare to China which in turn increases the attractiveness of investment.

⁴ Good News, Bad News, Volatility, and Betas

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Annexure

The Residuals of CNX Nifty and Shanghai Composite over the study period is given separately in the graph.

Fig.2

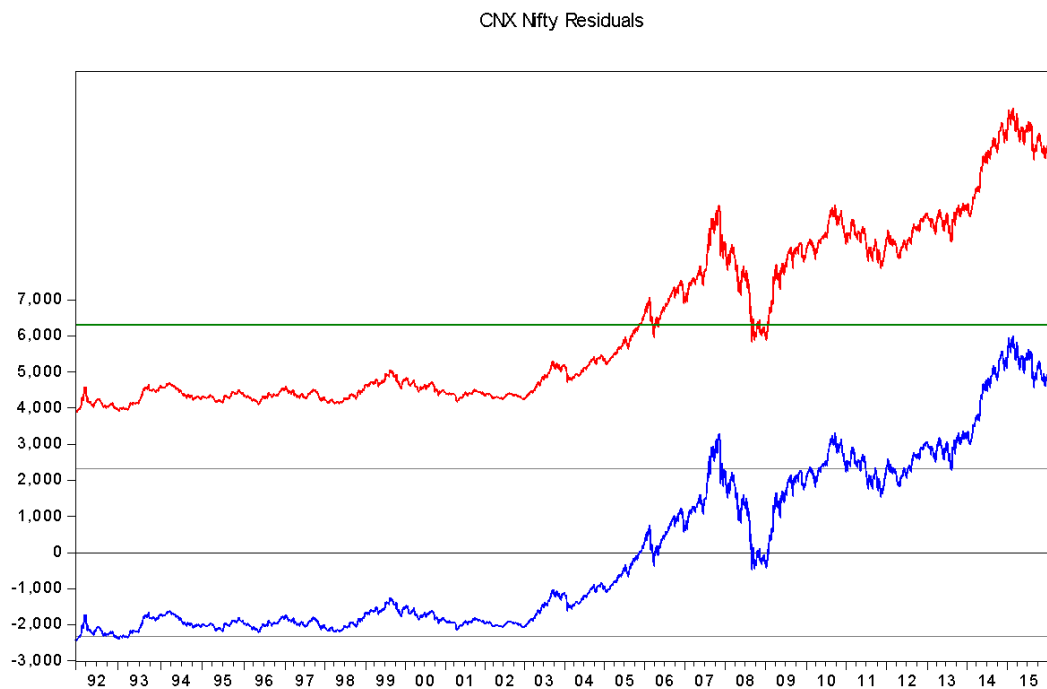


Fig.3

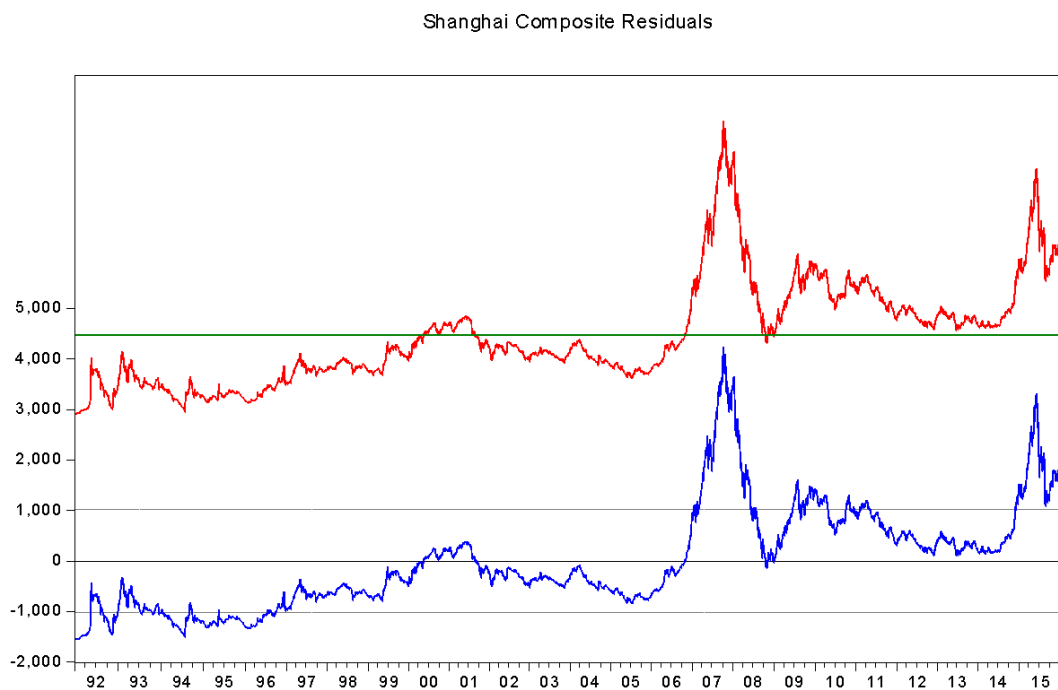


Fig 4 & 5

Seasonal fluctuations of return of indices for Whole Study Period

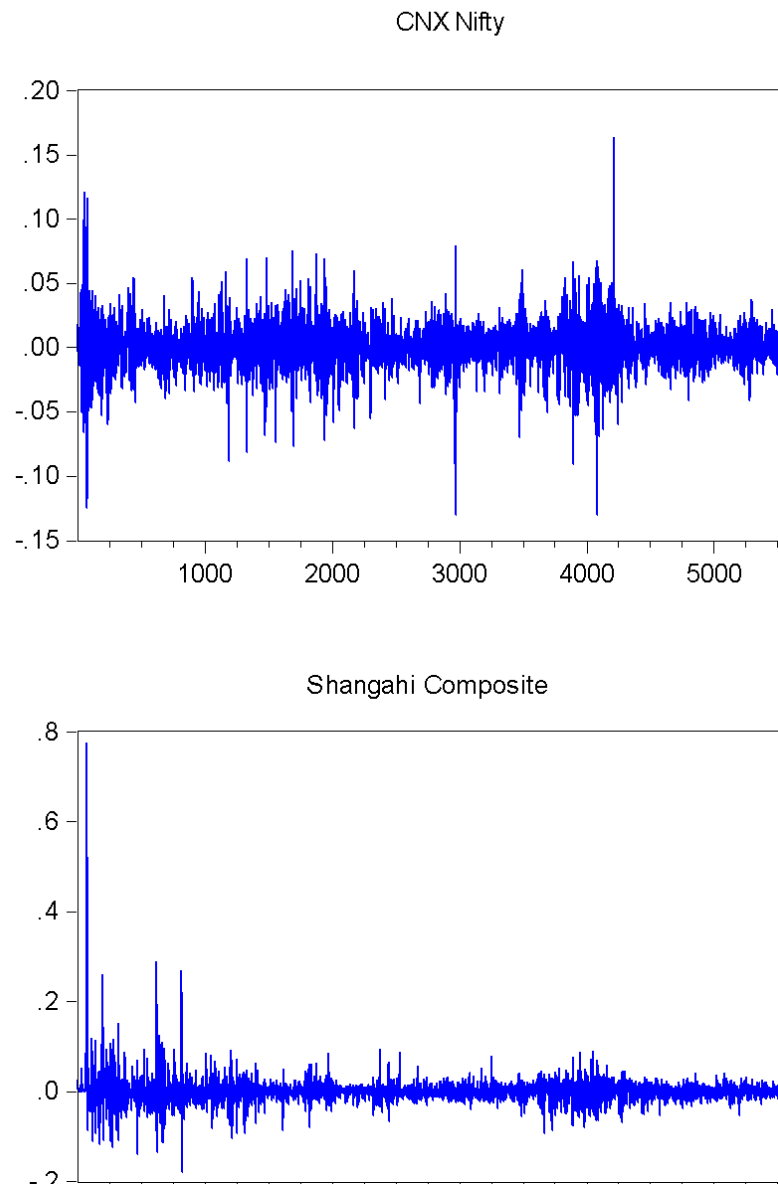


Fig 6 & 7

Pre crisis Period

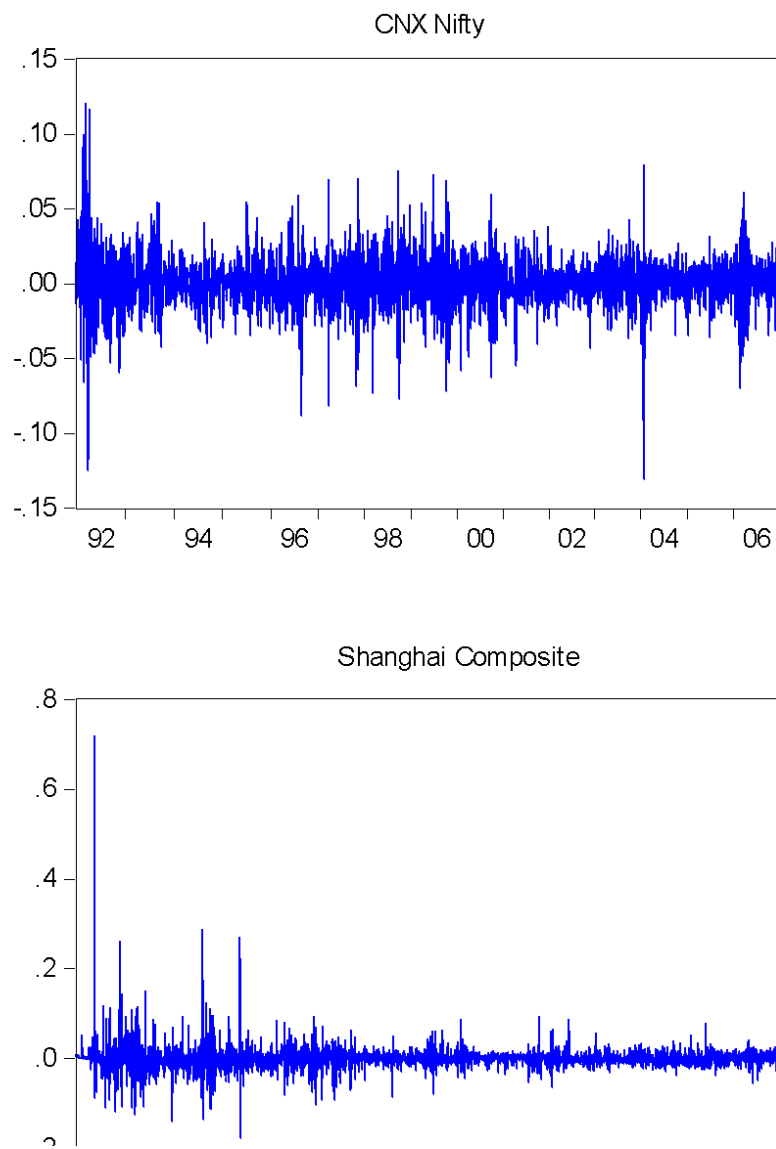


Fig 8 & 9

Post Crisis Period

