ISSN: 2278-0181
NCETEMS-2015 Conference Proceedings

Empirical Estimates of Stock Markets in Emerging Economies: A Special Reference with Asymmetric Effect

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Abstract: **The study analyses the asymmetric effect of GARCH framework in stock markets of10 emerging economies-Taiwan, Brazil, South Korea, China, India, Malaysia, Mexico, Philippines, Indonesia, Russia and 2 developed economies-Japan and USA for a period beginning 1st January 1997 through 30th June 2011. Data have been analyzed with the help ofpower-GARCH econometric tool.The study findsvolatility in emerging markets as well as developed markets shows long term persistence. The empirical results present in the study shows that there isasymmetric volatility in both the markets. But asymmetric effect in emerging markets is somewhat larger than that of mature markets.**

Key Words: Volatility, Asymmetric Effect, Emerging Economies.

I. INTRODUCTION

Financial markets play an important role in the process of economic growth and development by facilitating savings and channelling funds from savers to investors.With a view to know the risk returns of global diversification, this study presents the volatility in the international scenario. Volatility is one of the most important aspects of financial market developments providing an important input for portfolio management, option pricing and market regulations (Poon and Granger, 2003). Substantial changes in volatility of stock markets' returns can have significant negative effects on risk averse investors. In the face of global integration of financial markets, challenges posed by emerging transition economies and possible benefits of regional integration, there is great need to constantly determine the characteristics of both the developed and emerging markets.Investment opportunities can therefore arise from this abnormal behaviour and portfolio managers may want to rebalance their portfolios from one market to another as the risk reduction envisaged depends on the negative correlation of stock markets return and volatility. The degree of stock market volatility can help forecasters predict the path of an economy'sgrowth and the structure of volatility can imply that " investors now need to hold more stocks in theirportfolio to achieve diversification" [Krainer, J, (2002:1)].

Other financial professionals, such as risk managers, need to have a thorough understanding of how markets behave so that they can develop effective strategies for hedging against economic shocks. However, there is far less agreement on the causes of changes in stock market volatility. Some economists see the causes of volatility in the arrival of new, unanticipated information that alters expected returns on a stock (Engle and Ng, 1993). Thus, changes in market volatility would merely reflect changes in the local or global economic environment.

In most of the cases theARCH and GARCH models are apparently successful in estimating and forecastingof volatility on financial time series data, but they cannot capture some importantfeatures of the data.The mostinteresting feature not addressed by these models is the asymmetric effectwhere the conditional variance tends to respond asymmetricallyto positive and negative shocks in errorsdiscoveredby Black (1976), and confirmed by the findings of French, Schwert andStambaugh (1987), Schwert (1990), and Nelson (1991), among others. There are several conditional volatility models like E-GARCH, T-GARCH which can be used tomodel asymmetry and each fits the data differently and implies a somewhatdifferent news impact curve. Recently, Mittnik and Paolella (2000)and Giot and Laurent (2003) have suggested that a power-GARCH model(Ding et al. 1993) should be used to measure risk in currency and equity stock markets because the power-GARCH model nests many other generalisedautoregressive conditional heteroscedasticity (GARCH)-type models. Forexample, the power-GARCH model nests the GARCH model of Bollerslev(1986), which features a conditional variance equation, as well as the modelof Taylor (1986), which features a conditional standard deviation equation.A power-GARCH model also nests familiar asymmetric volatility modelssuch as threshold generalised autoregressive conditional heteroscedasticity(TGARCH) and EGARCH (Hentschel 1995). Mittnik and Paolella (2000)and Giot and Laurent (2003) have also documented the fat-tailed distributions of unconditional returns and fit the power-GARCH model using eithera *t*-distribution or a skewed *t*-distribution

The presence of asymmetric volatility can be tested by the null hypothesis $H0$: $\Upsilon = 0$. The impactis asymmetric if$\Upsilon \neq 0$ or we can say significantly different from zero.

There exists a broad literature on the research done on stock market volatility in the stock markets all around the world. However, there exists only little study that addresses the emerging markets' status in terms of volatility in stock returns. Almost all of the literature focuses on a group of developed countries. For instance, Eun and Shim (1989) analysed daily stock market returns of Australia, Hong Kong, Japan, France, Canada, Switzerland, Germany, US and the UK; whereas, Ng (2000) examines the magnitude and changing nature of volatility spillovers from Japan and the US to six Pacific-Basin equity markets. A few studies, such as Steely and Steely (1999), Gerrits and Yuce (1999), Yang et al. (2003), Syriopoulos (2004) and Apolinario et al (2006) studied European markets in general, and a few such as Jochum et al. (1999), Dockery and Vergari (2001), MacDonald (2001), *ChiakuChukwuogor& Mete Feridun*Gilmore and McManus (2002) focused on the Central Eastern countries.

II. LITERATURE REVIEW

Stock market volatility differs dramatically across international markets (Xing, 2004;Roll, 1992;Harvey, 1995;Bekaert and Harvey, 1997; Aggarwal et al., 1999). Cohen et al.'s(1976) results on US, UK and Japanese market evidenced the differences in returnvolatility as because of market thinness and share turnover. Emerging market equities have vastly different characteristics than equities fromdeveloped markets and these markets are characterized by high risk, high return, highpredictability and high volatility (Bekeart and Harvey, 1997). DeSantis and Imrohoroglu(1997) and (Sandeep and Sarkar, 1998) also noted that volatility is notoriously high in emerging stock markets comparedto developed markets. The aim of this paper is to examine the characteristicsof developed and emerging markets with reference to volatility.

(Sandeep and Sarkar, 1998) examined volatility behaviour in thirty-four markets, equally divided between developedand emerging markets, covering the period between 1993 and 2000. Emerging marketsreceive equal attention to developed markets because of the recent research findingswhich suggest that less liquid markets are particularly prone to volatility shocks. In addition, hedging strategies for investing in emergingmarkets are particularly valuable given the inherently high volatility in these countriesgenerally. A greater understanding of the interrelationships between market volatilityexposures could lead to more effective hedging activity in these countries.

The financial literature that offers research on market volatility over time among world markets is still unresolved. Researchers have empirically demonstrated (Harvey, 2001; Li, 2002) that the relationship between return and volatility depends on the specification of the conditional volatility.

Malkie and Xu (1999) used a disaggregate approach to study the behavior of stock market volatility. They explain while the volatility for the stock market as a whole has been remarkably stable over time, the volatility of individual stocks appears to have increased. Yu (2002) evaluates the performance of nine alternative models for predicting market volatility. The data set he used is the New Zealand Stock Exchange (NZSE40) capital index. The competing modelsincluded both simple models such as the random walk and smoothing models and complex models such as ARCH-type models and a stochastic volatility model. Four different measures are used to evaluate the SEF forecasting accuracy. The study found that the stochastic model provides the best performance among the alternatives; ARCH-type models can perform good or bad depending on form chosen the performance of the GARCH (3,2) model; and the best model within the ARCH-family is sensitive to the choice of assessment measures.

Li (2002) examined the relationship between expected stock returns and volatility in the 12 largest international stock markets. Consistent with the most previous studies, he finds the estimated relationship between return and volatility sensitive to the way volatilities are examined. When parametric EGARCH-M models are estimated, ten out of 12 markets have positive but statistically insignificant relationship. On the other hand, using a flexible semi-parametric test specification of conditional variance, he finds a negative relationship between volatility and return in most of the markets. Batra(2004) examined the time variation in volatility in the Indian stock market. He used the asymmetric GARCH methodology augmented by structural changes. Batra identifies sudden shifts in the stock price volatility and nature of events that cause these shifts in volatility.Karmakar (2005, 2006); Kaur (2002, 2004); Pandey (2005);Pattanaik and Chatterjee (2000) and Thomas (1995, 1998) have also used ARCH/GARCH model and its various extensionsin the Indian stockmarkets. Shenbagaraman(2003) has examined the impact of introduction ofindex futures and options on the volatility of underlying stock index in Indiausing a GARCH model.

Shin (2005) examined the relationship between risk and return in a number of emerging stock markets. The main contribution of Shin's (2005) paper is to present more reliable evidence on the relationship between stock market volatility and returns in emerging market by exploiting a recent advance in nonparametric modeling of conditional variance. This study employed both a parametric and semi-parametric GARCH models for the purpose of estimation and inference. The findings of their study also suggest fundamental differences between emerging anddeveloped markets.MollahSabur and MobarekAsma(2009) investigated the time-varying risk return relationship and the persistence of shocks to volatility within GARCH framework both in developed and emerging markets. The study uses nonlinear ARCH and GARCH-family models for testing the volatility both in developed and emerging markets. The findings of the paper suggest that there is a long-term persistence shock in emerging markets compared to developed markets

Campbell and Hentschel (1992) explain asymmetric volatility as volatilityfeedback which occurs when increases in volatility raise required stock returnsso that there is changing risk aversion. However, while changingrisk aversionis relevant on the scale of changes in market fundamentals, asymmetricvolatility is often found only with higher frequency data, as noted above.Campbell and Hentschel also show that variance increases morethan proportionally with the level of conditional variance in the most widelyused autoregressive conditional heteroskedasticity models, which lead tothe interesting hypothesis that asymmetry may be more important at highlevels of volatility. Like Campbell and Hentschel (1992)-Selcuk (2005);Mittnik and Paolella (2000); Giot and Laurent (2003);Bekaert and Wu (2000); Wu (2001); Bollerslev and Zhou (2006); Vorkink (2004);Spyrou (2005);Taylor (2005);A.Vramov et al. (2006); andShamilaJayasuriya, William Shambora and Rosemary Rossiter (2009) also concluded study on asymmetric effects and most of the above found significant asymmetric effects in their study.

Overall, the empirical research on volatility has been focused on different angles. However, from the previous literature review, it is suggested to know the characteristics of the stock markets in the global context that might help to explore the avenues of further research on the diversification among countries. Hence, this study aims to resolve few research questions such as:

1. Whether emerging markets are more predictable than developed markets.

2. Whether emerging markets are more volatile than developed markets.

3.Whether emerging markets are more asymmetric volatile than developed markets.

This paper attempts to take the insight into (above three questions)volatility and to explore the asymmetric volatility and a comparison between the developed and emerging markets, which might be helpful for risk management. Moreover, it could play a vital role for the development of market regulations across the countries.In this paper, we use an asymmetric PARCH model to measure the magnitude of asymmetric volatility for 10emerging markets and two mature markets.Using above models volatility betas and asymmetric effects areestimated which were uniformly positive and statistically significant. The emergingmarkets volatility betas are generally higher compared to the corresponding developedcountry exposures.

III. RESEARCH METHODOLOGY

To investigate the issue of stock market volatility, this study used MSCI (Morgan Stanley Capital International, Inc.) indexes of 12 countries that include 2developed and 10 emerging markets. Daily stock price indices in domestic currency for these countries exhibit are extracted from MSCI database.

Table 1: Exhibit-1

Country	Stock index	Exchange	Source
Brazil	BVSP INDEX	BOVESPA SAO PAULO Stock Exchange	World Federation Exchanges
Russia	RTSI	RTS exchange	www.allstocks.com
India	S&P CNX Nifty	National Stock Exchange	www.nseindia.com
Mexico	IPC	Bolsa Mexican Valores,(BMV)	www.allstocks.com
China	SSE	Shanghai Stock Exchange	www.yahoo.com
Indonesia	JKSD	Jakarta Stock Exchange	www.allstocks.com
South Korea	KOSPI	Korea Stock Exchange	World Federation Exchanges
Taiwan	TWSE	Taiwan stock Exchange	www.yahoo.com
Philippines	PSI	Philippines Stock Exchange	World Federation Exchanges
Malaysia	KLSI	Kaula Lumpur Stock Exchange	www.allstocks.com
U.S.	S&P 500	New York Stock Exchange	www.allstocks.com
Japan	NIKKEI-225	Tokyo Stock Exchange	www.allstocks.com

The sample period covers 1stJune, 1997 to 30th June 2011. To make the series stationary the study uses the daily return by logarithm method on daily close prices of the stock index and then apply further analysis.

Data have been analyzed using PARCH. The analysis of econometrics can be performed on a series of stationary nature. Therefore, to begin with study checks the stationary nature of the series by preparing line graphs. Further, we perform the Augmented Dickey-Fuller test under the unit root test to finally confirm whether or not the series are stationary. For the basic understanding of Unit root testing, we may look at the following equation:-

$$y_t = \rho y_{t-1} + x_t'\delta + \varepsilon_t , \qquad (1)$$

where$x_t$are optional exogenous regressors which may consist of constant, or a constant and trend, $\rho$and $\delta$are parameters to be estimated, and the $\varepsilon_t$are assumed to be white noise. If$|\rho| \geq 1$, y is a nonstationary series and the variance of y increases with time and approaches infinity. If$|\rho|<1$,y is a (trend) stationary series. Thus, we evaluate

ISSN: 2278-0181
NCETEMS-2015 Conference Proceedings

the hypothesis of (trend)stationarity by testing whether the absolute value of $|\rho|$ is strictly less than one.

where$\alpha = \rho - 1$. The null and alternative hypotheses may be written as,

$$H_0 : \alpha = 0 \qquad (2)$$

$$H1 : \alpha < 0 \qquad (3)$$

In order to make the series stationary, we determine the log of the twelve series and arrive at the daily return of the twelve series. All the remaining analysis is performed at the daily return (log of the series) of the twelve exchanges. We name these variables as follows: Rtaiwan, Rbrazil, Rsouth Korea, Rchina, Rindia, Rmalaysia, Rmexico, Rmhilippines, Rindonesia, Rrussia, Rjapan and Rusa.

Engle (1982) proposes to model time-varying conditionalvariance with the Auto Regressive Conditional Heteroscedasticity (ARCH) processthat uses past disturbances to model the variance of the series. Autoregressive Conditional Heteroskedasticity (ARCH) models are specifically designed tomodel and forecast conditional variances. The variance of the dependent variable is modelled as a function of past values of the dependent variable and independent or exogenousvariables.Early empiricalevidences show that high ARCH order has to be selected in order to catch thedynamics of the conditional variance. The Generalized ARCH (GARCH) modelof Bollerslev (1986) is an answer to this issue.ARCH models were introduced by Engle (1982) and generalized as GARCH (GeneralizedARCH) by Bollerslev (1986) and Taylor (1986). These models are widely used in variousbranches of econometrics, especially in financial time series analysis.

The estimation of GARCH model involves the joint estimation of a mean and a conditionalvariance equation. The simplest GARCH(1,1) specification applied in table 3:-

$$Y_t = X_t' \Theta + \mathcal{E}_t \qquad (4)$$

$$\sigma^2_t = \omega + \alpha\, \mathcal{E}^2_{t-1} + \beta \sigma^2_{t-1} \qquad (5)$$

In which the mean equation given in (4) is written as a function of exogenous variableswith an error term. Since is the one-period ahead forecast variance based on past information, it is called the *conditional variance*. The conditional variance equation specified in (5) is a function of three terms:

• A constant term:ω.

• News about volatility from the previous period, measured as the lag of the squared

residual from the mean equation: $\mathcal{E}^2_{t-1}$(the ARCH term).

• Last period's forecast variance:σ^2_{t-1}(the GARCH term).

The (1, 1) in GARCH(1, 1) refers to the presence of a first-order autoregressive GARCH term(the first term in parentheses) and a first-order moving average ARCH term (the second term in parentheses). To complete the basic ARCH specification, we require an assumption about the conditional distribution of the error term $\mathcal{E}$. There are three assumptions commonly employed when working with ARCH models: Normal (Gaussian) distribution, Student's *t*-distribution, and the Generalized Error Distribution (GED). Given a distributional assumption, ARCH models are typically estimated by the method of maximum likelihood. For the GARCH(1, 1) model we used normal (Gaussian) distribution or conditionally normal errors.

The ARCH test is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals (Engle 1982). This particular heteroskedasticity specification was motivated by the observation that in many financial time series, the magnitude of residuals appeared to be related to the magnitude of recent residuals. ARCH in itself does not invalidate standard LS inference. However, ignoring ARCH effects may result in loss of efficiency.

IV. PARCH

This model along with other models generalised in Ding et al. (1993) with Power ARCH specification. Who suggest that the second conditional moment equation of an asymmetric power-GARCH model should be written as:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}\right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta,$$

Where $\delta > 0$, $\gamma <= 1$ for i = 1,……..,r,$\gamma_i = 0$ for alli>r and r< = p.

In equation six $\varepsilon$is the error term, γ is the asymmetric term and δ is a power transformation that can be estimated from the data or restricted to take values such as 1 or 2. Hentschel (1995) uses a Box–Cox transformation to prove that the power-GARCH model is a member of a large family of conditional variance equations.In thisarticle, we use the BIC criterion to select the nested model which best fitsthe data for a given subsample.

As is done virtually in all of the literature, we assume a parsimonious versionof the asymmetric power-GARCH model, that is to say, an asymmetricpower-GARCH (1,1) model with $p = q = 1$. Mittnik and Paolella (2000); Giot and Laurent (2003) and ShamilaJayasuriya et.al.(2009) estimate this model (or its symmetric volatilitycounterpart) in their studies with a *t*-distribution or a skewed *t*-distribution, which may bean appropriate choice when seeking to measure including longandshort-trading positions. For our objective to study, we also estimate the model assuming aconventional *t*-distribution and the calculation method is as follows:

$$l_t = -1/2 \log [\pi(v-2)\, \Gamma\, (v/2)^2 / \Gamma\, ((v+1)/2)^2]^{-}1/2 \log \sigma^2_t - (v+1)/2 \log [\, 1 + (y_t - X_t \Theta)^2 / \sigma^2_t (v-2)] \qquad (7)$$

where the degree of freedom $v>2$ controls the tail behavior. The *t*-distribution approaches the normal as $v \rightarrow \infty$.

ISSN: 2278-0181

V. ANALYSIS

Table 2 presents the result of ADF-unit root test and line graph respectively on return series of underlying stock markets namely:Rbrazil, Rrussia, Rindia, Rmexico, Rchina, Rphilippines, Rsouth Korea, Rtaiwan, Rindonesia, Rmaleysia, Rusa, and Rjapan.

Null Hypothesis: individual return series has a unit root		RBRAZIL	RRUSSIA	RINDIA	RMEXICO	RCHINA	RPHILIPPINES	RSOUTH KOREA	RTAIWAN	RINDONESIA	RMALAYSIA	RUSA	RJAPAN
Prob.*	ADF Test Statistic	-38.42	-30.56	-36.24	-36.88	-35.68	-34.91	-36.87	-35.50	-35.28	-25.84	-38.89	-38.95
	Prob.*	0	0	0	0	0	0	0	0	0	0	0	0
Test critical values:	1%	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.431446
	5%	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86192
	10%	-2.57	-2.57	-2.57	-2.57	-2.57	-2.57	-2.57	-2.57	-2.57	-2.57	-2.57	-2.56701

The ADF test result values of all stock return series given below aresignificant at 0.001 percent it means return seriesdoes not have a unit root. Further, the statistic values are less than the all critical values at the 1%, 5%, and 10% so that it also ensures, we can reject the null hypothesis and confirms all of the stock market return series has not a unit root and that are stationary.

Table 3 reports the result of GARCH(1,1) model estimation for stock returns, which refers to First-order autoregressive GARCH term (the first term in parentheses) and a first- order Moving average ARCH Term(the second term in parentheses). The ARCH LM test statistic and LB – Q statisticsare used for fitness of order specification. The p values in ninth column of table 3 for Obs*R-squared statistic by Engle's LM test statistic is computed from the test regression. As p – value of Obs*R-squared coefficients is greater than 0.05 at all rows so we cannot reject the null hypothesis(there is no ARCH up to order q in the residualsi.e. q=1 in model) at 5% for all countries and we can say that (1,1) order is sufficient for ARCH and GARCH Parenthesis which found no ARCH term in residuals and confirms the above that the GARCH (1, 1) model is adequate. The result of SIC for level of model selection is also supported by the results of Karmakar, Madhusudan (2007).Highly insignificant p- value of LB-Q statistic reports in column eleventh support the result of ARCH LM test that there is no ARCH term in residuals. Coefficient of Autocorrelation also shows no ARCH term left in residuals.

First column of table 3shows the name of countries and second column (ω) shows the estimated coefficients of constant. The third and fourth columns report the estimated coefficients for (α) ARCH term and (β) GARCH term respectively. Furthermore, the persistence of the conditional volatility, measured by (α+ β).The p-value of the coefficients is shown in ()parentheses and standard errors are shown in [ ]. Estimated values for theα and β coefficients are reasonable and highly significant for all markets. In the estimation of volatility, the α coefficient represents theweight applied to news measured as last period's shock, so that the larger the α coefficient the more a market reacts to news. The β coefficient representsthe weight applied to the previous forecast of volatility.

The estimated coefficients for (α) ARCH term and (β) GARCH term are statistically significant for all stock markets in the sample at 1% level. (β) GARCH term for each country is larger than (α) ARCH termimpling that large market surprises induce smaller revisions in future volatility. The α coefficients ranges from 0.062102 (China) to 0.178934 (Russia), While the β coefficients ranges from 0.798115 (Philippines) to 0.928840 (China).In numerous studiesof mature markets, it is common to observe reaction coefficients (α 's) of less than 0.10 and β coefficients of approximately 0.90, especially for daily data.Comparing mature and emerging markets, we see that emerging markets often have larger α coefficients and smaller β coefficients. Thus, emerging marketsoften react somewhat more to news (have more spiky GARCH volatilities),a result consistent with Alexander (2001),Jayasuriya*et. al* (2009). Our results are also comparable with the results of Lamouresux and Lastrapes (1991) and Omran and Mckenzie(2000) who, reports a high degree of volatility persistence in their studies.

Obtaining a value of β>0 along with a value of (α+ β) less than unity (except Russia) suggests the existence of a stationary process. This would imply that current information can be used in predicting future volatility.

Table 3: GARCH (1,1) Estimation Results

	Ω	α	B	α+β	Logs likelihood	Durbion-Wast	No. of Observation	P-Value on ARCH LM Test	SIC	LBQ(1)p-value	AC
BRAZIL	0.0000119 (0.0000) [1.78E-06]	0.1106 (0.0000) [0.006816]	0.86445 (0.0000) [0.009373]	0.98	9235	1.95	3641	0.06	-5.06	0.3138 (0.575)	-0.01
RUSSIA	9.01E-06 (0.0000) [8.31E-07]	0.178934 (0.0000) [0.00909]	0.847167 (0.0000) [0.006490]	1.03	10271	1.77	4356	0.40	-4.78	0.7199 (0.396)	0.01
INDIA	9.21E-06 (0.0000) [6.74E-07]	0.128285 (0.0000) [0.006611]	0.846685 (0.0000) [0.006370]	0.97	10069	1.88	3653	0.83	-5.50	0.0008 (0.978)	0.00
MEXICO	3.80E-06 (0.0000) [5.63E-07]	0.113586 (0.0000) [0.005664]	0.876542 (0.0000) [0.006295]	0.99	10579	1.83	3690	0.21	-5.73	1.5523 (0.213)	0.02
CHINA	2.62E-06 (0.0000) [3.56E-07]	0.062102 (0.0000) [0.003397]	0.928840 (0.0000) [0.003096]	0.99	8411	1.99	2998	0.70	-5.60	0.1483 (0.700)	0.01
PHILIPPINES	1.95E-05 (0.0000) [1.26E-06]	0.122864 (0.0000) [0.005884]	0.798115 (0.0000) [0.009318]	0.92	10105	1.74	3576	0.52	-5.64	0.4237 (0.515)	0.01
SOUTH KOREA	1.99E-06 (0.0001) [4.97E-07]	0.084424 (0.0000) [0.007010]	0.914964 (0.0000) [0.006789]	1.00	9271	1.87	3504	0.45	-5.28	0.5628 (0.453)	-0.01
TAIWAN	2.51E-06 (0.0000) [5.03E-07]	0.081545 (0.0000) [0.006317]	0.911614 (0.0000) [0.006716]	0.99	9863	1.90	3499	0.21	-5.63	1.5692 (0.210)	-0.02
INDONESIA	9.37E-06 (0.0000) [8.66E-07]	0.137274 (0.0000) [0.008104]	0.839216 (0.0000) [0.007596]	0.98	9508	1.70	3455	0.36	-5.49	0.8326 (0.362)	0.02
MALAYSIA	1.09E-05 (0.0000) [2.76E-07]	0.126468 (0.0000) [0.005105]	0.820689 (0.0000) [0.004267]	0.95	10962	2.06	3632	0.36	-6.03	0.8542 (0.355)	0.02
USA	1.70E-06 (0.0000) [2.38E-07]	0.089267 (0.0000) [0.006428]	0.902479 (0.0000) [0.007214]	0.99	11439	2.15	3704	0.03533*	-6.17	4.2793 (0.039)	-0.03
JAPAN	5.02E-06 (0.0000) [9.24E-07]	0.106157 (0.0000) [0.007935]	0.875976 (0.0000) [0.009633]	0.98	10229	2.07	3612	0.85	-5.65	0.0356 (0.850)	0.00

Note: p-value in ( ) parentheses and Standard Errors in [ ].

In this article, we use an asymmetric power-GARCH model (Table-4) to measure the magnitude of asymmetric volatility for 10 emerging markets and 2 mature markets.

Estimated values for the α and β coefficients are reasonable and highly significant for most markets. The *P*-value for α for the USA is (0.9441). In the estimation of volatility, the α coefficient represents theweight applied to news measured as last period's shock, so that the larger the α coefficient the more a market reacts to news. The β coefficient representsthe weight applied to the previous forecast of volatility. In numerous studiesof mature markets, it is common to observe reaction coefficients (α's) of less than 0.10 and β coefficients of approximately 0.90, especially for daily data, same results also supported here.Comparing mature and emerging markets, we see that emerging markets often have larger α coefficients and smaller β coefficients. Thus, emerging marketsoften react somewhat more to news (have more spiky GARCH volatilities),a result consistent with Alexander (2001).The focus of this article is the magnitude of asymmetric volatility estimatedfor each market because the more asymmetric a market the higher the risk. The γ coefficient for the USA is not statistically significant(0.9441) and a symmetric and this result is against ofthatlarge body of literature which has consistently provided evidence ofasymmetry for the UScall the market asymmetric. Market of Japan exhibits asymmetric volatility and*P*-value is 0.0000. In the case of the emerging markets, all markets areasymmetric based on statistically significant estimates of the γ coefficients.

Table 4: Power ARCH [parch (1,1)] Estimating Results

	Ω	ϒ	α	β	Logslikelihood	Durbion-Wast	BIC	Q(1) p-value	AC
BRAZIL	1.32E-05 (0.0000) [2.18E-06]	0.526937 (0.0000) [0.129299]	0.068013 (0.0000) [0.014255]	0.878248 (0.0000) [0.013308]	9325.045	1.952540	-5.108731	3.7628 (0.052)	-0.032
RUSSIA	0.000529 (0.0000) [9.92E-05]	0.149899 (0.0031) [0.050731]	0.134704 (0.0000) [0.012174]	0.876553 (0.0000) [0.011036]	8873.495	1.730371	-4.821998	2.0748 (0.150)	0.024
INDIA	0.000786 (0.0000) [0.000107]	0.455447 (0.0000) [0.061204]	0.132344 (0.0000) [0.011817]	0.845116 (0.0000) [0.01283	10227.35	1.880646	-5.588198	0.0181 (0.893)	-0.002
				9]					
MEXICO	0.000321 (0.0000) [5.36E-05]	0.598430 (0.0000) [0.081477]	0.095784 (0.0000) [0.010287]	0.904156 (0.0000) [0.009468]	10711.42	1.832252	-5.792292	0.5186 (0.471)	0.012
CHINA	0.000225 (0.0004) [6.35E-05]	0.230581 (0.0000) [0.067167]	0.087330 (0.0006) [0.010538]	0.925088 (0.0000) [0.008883]	8567.758	1.984696	-5.699627	0.0007 (0.979)	0.000
PHILIPPINES	0.000969 (0.0000) [0.000168]	0.205773 (0.0000) [0.053681]	0.151954 (0.0000) [0.015508]	0.823143 (0.0000) [0.018998]	10414.87	1.737547	-5.811146	1.0761 (0.300)	0.017
SOUTHKOREA	0.000185 (0.0000) [4.39E-05]	0.405457 (0.0000) [0.066996]	0.086243 (0.0000) [0.009111]	0.924224 (0.0000) [0.007815]	9345.474	1.868787	-5.320199	0.6019 (0.438)	-0.013
TAIWAN	0.000232 (0.0000) [4.8	0.508248 (0.0000) [0.080437	0.074624 (0.0000) [0.0	0.927202	9951.98	1.896481	-5.6744	1.1666 (0.28	-0.018

	2E-05]	]	08606]	(0.0000) [0.080437]	0		78	0)	
INDONESIA	0.000867 (0.0000) [0.000147]	0.380691 (0.0000) [0.058202]	0.148415 (0.0000) [0.015019]	0.838875 (0.0000) [0.016156]	9667.800	1.706734	-5.579903	0.4926 (0.483)	0.012
MALAYSIA	0.000245 (0.0000) [4.34E-05]	0.259274 (0.0000) [0.047786]	0.155681 (0.0000) [0.012988]	0.866409 (0.0000)	11733.08	2.061058	-6.447406	5.3755 (0.020)	0.038

				[0.010535]					
USA	5.18E-05 (0.1794) [3.86E-05]	1.000000 (0.9441) [14.27304]	0.060358 (0.9120) [0.545901]	0.927607 (0.0000) [0.08413]	11565.78	2.154630	-6.229491	9.1460 (0.002)	-0.050
JAPAN	0.000387 (0.0000) [6.58E-05]	0.641535 (0.0000) [0.094202]	0.081017 (0.0000) [0.009497]	0.910896 (0.0000) [0.09481]	10292.04	2.074999	-5.687465	0.0959 (0.757)	-0.005

Notes: p-value in ( ) parentheses and Standard Errors in [ ].

The question which arises, naturally, is what a possible explanation for thesefindings could be? Black (1976) and Christie (1982) were the first todocument and explain the asymmetric volatility property of individual stockreturns in the US stock markets. This articlesexplain the leverage effect hypothesis: A drop in the value of the stock (negative return)increases financial leverage, which makes the stock riskier and increases its volatility.Although, to many, ‘leverage effects’ have become synonymous with asymmetricvolatility, the asymmetric nature of the volatility response to return shockscould simply reflect the existence of time-varying risk premiums [Campbelland Hentschel (1992), French, Schwert and Stambaugh (1987) and Pindyck(1984)]. If volatility is priced, an anticipated increase in volatility raises the requiredreturn on equity, leading to an immediate stock price decline. This isoften referred to as the ‘volatility feedback effect’.In fact, the leverage effect and the volatility feedback effect could both be atwork. Suppose there is an event which has raised traders’ expectation of volatilityin future. The effect of such volatility shock is often reflected in traders’ reluctanceto buy and willingness to sell in anticipation of a volatile market. As a result,stock prices have to drop to balance the buying and selling volume. Thusan anticipated increase in volatility leads to an immediate price drop, as predictedby the volatility feedback hypothesis. This drop in stock price raises the leverageratio, which by the leverage effect hypothesis brings about a further increase involatility and therefore a further drop in price. This process can go on indefinitely.Bekaert and Wu (2000) examined asymmetric volatility in the Japanese equitymarket and concluded that volatility feedback was the dominant cause of theasymmetry [KarmakarMadhusudan(2007)].

VI. CONCLUSION

The volatility of Stock marketdiffers dramatically across international markets as because of market thinness and share turnover [Harvey (1995); Aggarwal et.al. (1999); Cohen et.al. (1976)]. In that direction this study investigatesthe asymmetric effect within GARCH framework both in developed and emerging markets. This study finds the predictability of stock market is higher inemerging markets than the developed markets. The major finding of the study is that the alpha coefficient of the emerging economies is higher compared to the developed economies that indicate inefficiency in the emerging markets. Long term persistency of volatility finds both in emerging markets as well as developed markets as ($\alpha + \beta$)

close to 1 or greater than 1 that shows increasing tendency rather than decay overtime.Engle (2004) shows that equity markets are moreriskier when volatility is asymmetric.The empirical results of this article confirm that there isasymmetric volatility inboth the markets emerging as well as developed markets. But asymmetric effect in emerging markets is somewhat larger than that of mature markets.

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