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Modeling Return Volatility of Bric Emerging Stock Markets Using Garch Family Models

KEYWORDS: GARCH models, emerging markets, volatility, financial crisis, international portofolio diversification

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ABSTRACT *This article aims to highlight a controversial issue of great interest ie the intrinsic structure of emerging capital market behavior. Synthesizing, empirical analysis aims to analyze emerging capital markets volatility. Emerging capital markets establish a separate category in the financial field, with highly dynamic characteristics, especially in times of financial crisis. Emerging capital markets are extremely attractive considering the growth prospects and investment opportunities. However, volatility of returns is significant and represents an undeniable obstacle in attracting investors. Modeling and forecasting volatility of emerging capital markets is still an underexploited area although it has quite interesting research resources. Stock prices volatility can be used as a measure of risk in financial markets, so its importance is even greater in emerging capital markets. A sharp introspection regarding cointegration of emerging stock markets raised significant issues as a direct consequence of international portofolio diversification and financial globalization.*

INTRODUCTION

Generally, the analysis of financial time series is based on unpredictable stochastic variables and assets price movements are perceived as random processes. Despite many open questions, emerging capital markets behavior is apparently a symbiotic mechanism triggered by deterministic and stochastic processes. The concept of volatility represent a very fertile habitat for research with profound implications in areas of interest such as investment optimization, international portfolio diversification, financial derivative strategies, options trading, foreign exchange rate market, risk management and financial asset pricing. As a profane expression, volatility represents the conditional variance of the underlying financial asset returns. The estimation process of conditional variance express a special significance considering the fact that forecasting volatility is an essential aspect of the investment process. As a consequence of the fact that volatility can not be directly identified, the literature consecrated certain stylized facts. The process of modeling and forecasting stock markets behavior is significantly influenced by: volatility clustering, leverage effect, leptokurtosis, skewness, heteroscedasticity. The behavior of volatility in time requires a continuous evolving, so it is excluded the existence of volatility jumps. Generally, a decrease in stock returns causes an increase in volatility higher compared with the case when volatility is generated by an increase in stock returns. Summarizing, volatility seems to react differently in terms of great positive or great negative returns. Moreover, volatility does not diverge to infinity.

METHODOLOGICAL APPROACH

This study follows application of GARCH models and includes GARCH (1, 1) which was introduced by Engle (1982) further it is extended by Bollerslev (1986) and again by Nelson (1991), Exponential GARCH or EGARCH which is introduced by Nelson (1991) and GJR-GARCH proposed by Glosten, Jagannathan and Renkle (1993). GARCH (1, 1) is the simplest form to represent heteroskedasticity and EGARCH provides confidence for positivity of conditional variance. It covers the asymmetric impact and strongly confirms leverage effect. GJR-GARCH represents dummy variable using original GARCH model. It targets asymmetric in terms of negative and positive shocks. The empirical analysis is based on certain financial time series which represents daily closing prices of main indices of BRIC stock markets (Brazil, Russia, India and China) from first day of trading in January, 2003 to last day of trading January, 2013, respectively 2497 observations. The selected stock indices are the following IBOVESPA (Brazil) RTS (Russia), BSE-SENSEX (India) and SSEC (China).

GARCH (1, 1) model

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$$

This is the most popular GARCH model and calculates weighted average of constant (ω), yesterday's forecast of closing indices (α_{1ut-1}^2) and represents ARCH term, and yesterday's squared error ($\beta_1 h_{t-1}$) and this represents GARCH term.

Exponential GARCH or EGARCH model

$$\text{Log } h_t = \omega + \beta_1 \log h_{t-1} + \alpha_1[\theta V_{t-1} + \gamma\{|V_{t-1}| - E|V_{t-1}|\}]$$

This model takes a long form and adds an additional term for leverage effect which we call as asymmetric effect. This model guarantees positive variance because of h_t= exp (R.H.S.) > 0 always and θV_{t-1} covers asymmetric effect.

GJR-GARCH model

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \theta I_{t-1} u_{t-1}^2$$

This model also provides leverage effect. Here if $\theta > 0$, we say that there is a leverage effect or otherwise. Here $I_{t-1} = 1$ if $u_{t-1} < 0$ and $I_{t-1} = 0$ or otherwise and if $\theta > 0$, we say that there is a leverage effect. This model is capable to tell us the effect of news on volatility. It reflects that bad news ($u_{t-1} < 0$) has an effect of $(\alpha_1+\theta)\ u_{t-1}^2$ on the variance. Where as good news ($u_{t-1} > 0$) has an effect of $\alpha_1\ u_{t-1}^2$ on the variance and if $\theta < 0$ represent effect of bad news. Application of model makes it easy to decide if $\theta = 0$ or $\theta > 0$ or not. In order to employ the previous models, it is necessary to investigate the sample financial time series stationarity or non-presence of unit roots. We have considered series log for all stock indices and computed first log difference to make it stationary. According to the following descriptive statistics, Skewness represents negative value and provides long tail, and this provides high kurtosis which reflects fat skewness. It suggests that all distributions are highly leptokurtic. Volatility clustering is present in all four cases without any exception. The closing price of stock index of China, seems to be extremely volatile among the other indices. The continuous volatility with low and high

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degree of fluctuations or volatility clustering entails that error exhibits heteroskedasticity. It suggests that unconditional standard deviations are not constant.

TABLE – 1 DESCRIPTIVE STATISTICS

Variance	BRAZIL-IBOVESPA	RUSSIA-RTS	INDIA-SENSEX	CHINA-SSEC
Basic Statistics				
Mean	0.0668424	0.0602754	0.0704324	0.0173870
Median	0.127544	0.175931	0.121207	0.00693064
Min	-12.0961	-21.1994	-11.8092	-9.25615
Max	13.6766	20.2039	15.9900	9.03425
Std Dev	1.84202	**2.25698**	1.63371	1.65548
Skewness	-0.0945921	-0.542471	-0.0771899	**-0.257509**
Kurtosis	5.20287	**11.1868**	7.87480	**3.66950**
Unit Root Test (tested at 10%, 5% and 1% = 0.119, 0.148, and 0.218)				
test stat	0.0313	0.0777	0.0488	0.155*

Source: Author's computation using stock indices
***ADF Test significant at level of 1%**

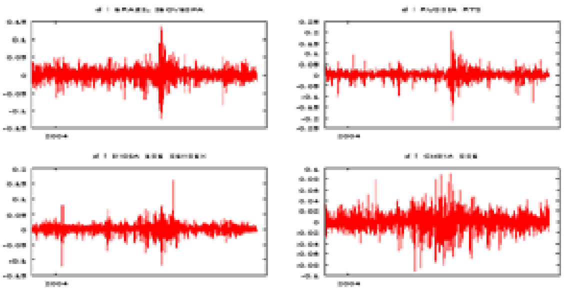

Figure 1 Log returns series of BRIC indices
Source: Author's computation using stock indices

TABLE – 2 GARCH FAMILY MODEL ESTIMATIONS

Index	Model/Vari	GARCH	EGARCH	GJR-GARCH
Brazil-IBOVESPA	Mean Equ.	0.000967453 (0.0014)	0.000503205 (0.00951)	0.000568184 (0.0609)
	Omega	6.63299e-06 (0.0001)	0.322863 (2.72e-08)	9.08142e-06 (1.07e-05)
	Alpha	0.0728818 (1.07e-012)	0.138249 (1.09e-01)	0.0529221 (1.13e-05)
	Gamma	---	0.0834122 (1.81e-010)	0.537831 (0.0004)
	Beta	0.904681 (0.0000)	0.973825 (0.0000)	0.899053 (0.0000)
Russia - RTS	Mean Equ.	0.00196445 (1.61e-09)	0.00178073 (6.51e-07)	0.00148133 (8.19e-06)
	Omega	1.22340e-05 (5.59e-09)	0.483377 (2.76e-015)	1.40661e-05 (1.71e-010)
	Alpha	0.119581 (4.32e-018)	0.201397 (7.52e-022)	0.100703 (4.87e-015)
	Gamma	---	0.0765830 (3.82e-010)	0.260053 (4.13e-07)
	Beta	0.854839 (0.0000)	0.958436 (0.0000)	0.855084 (0.0000)
India – BSE SENSEX	Mean Equ.	0.00124344 (1.21e-07)	0.000853940 (0.0002)	0.000944826 (7.48e-05)
	Omega	4.03070e-06 (6.90e-05)	0.448049 (2.23e-013)	5.26365e-06 (2.07e-06)
	Alpha	0.119082 (5.46e-018)	0.239011 (6.86e-027)	0.109041 (7.64e-016)
	Gamma	---	0.0780109 (9.78e-09)	0.263884 (5.45e-07)
	Beta	0.868298 (0.0000)	0.969322 (0.0000)	0.862396 (0.0000)
China - SSE	Mean Equ.	0.000180657 (0.0098)	0.000267190 (0.0004)	0.000124542 (0.0038)
	Omega	2.14310e-06 (0.0009)	0.165011 (1.20e-07)	2.36124e-06 (0.0009)
	Alpha	0.0493071 (1.41e-012)	0.112154 (1.24e-013)	0.0504766 (1.34e-012)
	Gamma	---	0.00607278 (0.0425)	0.0572012 (0.0329)
	Beta	0.942763 (0.0000)	0.990127 (0.0000)	0.940377 (0.0000)

Source: Author's computation using stock indices
Values in ( ) represent values of p
Significant at 1%

The presence of ARCH effect was confirmed by applying ADF test at level of 1%. Particularly for EGARCH and GJR-GARCH models, we note that negative value for correlation coefficient provides evidence for potential leverage effects. The GARCH (1, 1) model coefficient of lagged conditional variance (β_1) is significantly different from zero. That suggests indicating volatility clustering in all four time series.The sum of (α_1 + β_1) coefficient is a unity and suggests that shocks to the conditional variance are highly importunate. The (α_1) represents ARCH effect and (β_1) represents GARCH effect. We form (α_1 + β_1) equation for BRIC markets. The calculation of (α_1 + β_1) values for B.R.I.C. results Brazil (IBOVESPA) 0.9775628, Russia (RTS) 0.97442, India (BSE SENSEX) 0.98738, and China (SSE) 0.9920721. It suggests that a value most near to zero implies that violent shocks from a heavy blow is relatively slow speed attenuation. Thus we can conclude that ARCH term (α_1) represents effect of positive or good news with that degree of magnitude.

The asymmetric effect is examined by EGARCH and GJR-GARCH. Both models produces same results in terms of asymmetry and leverage effects. First we discuss about results from Exponential GARCH or EGARCH. It estimates leverage effect confidently from all BRIC markets. To understand the effect of EGARCH model, here the equation is given for one country (Brazil – IBOVESPA).

$$\text{Log } h_t = 0.322863\ (\omega) + 0.973825(\beta_1)\log h_{t-1} + 0.138249(\alpha_1)[\theta V_{t-1} + 0.0834122\ (\gamma)\{|V_{t-1}| - E|V_{t-1}|\}]$$

Moreover the value of (γ) is non zero, the Exponential GARCH (EGARCH) supports presence of leverage (asymmetry) in volatility of BRIC markets closing stock indices. It suggesting volatility of BRIC market indices are indicative and bad news has more powerful effect on volatility than good news. EGARCH model basically represents log of standard deviation or log of the variance as function of lagged logarithm of the variance or standard deviation, and lagged absolute error from regression model. This model allows response to the lagged error to be asymmetric. It suggests that our present investigation on BRIC market indices have different effect on variances. However, this model is limited to say about good news or bad news that which increases volatility. This aspect is captured by Threshold GARCH or TGARCH or GJR-GARCH. GJR-GARCH model is capable to measure effect of good news and bad news. We measure effect of good news ($u_{t-1} \geq 0$) has an effect of $\alpha_1\ u_{t-1}^2$ on the variance and if $\theta < 0$ represent effect of bad news. We apply this to finding out application of TGARCH on Brazil stock index as below.

$$h_t = 0.00000908142(\omega) + 0.0529221(\alpha_1)u_{t-1}^2 + 0.899053\ (\beta_1)\ h_{t-1} + 0.537831(\theta)I_{t-1}\ u_{t-1}^2$$

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The previous applied model shows that the good news has an impact of 0.0529 magnitudes where as bad news generates an impact of 0.0529+0.5378 = 0.5907 magnitudes. One can easily employ this practice on rest models with help of provided specimen of Brazil – IBOVESPA. Thus, we can conclude that identified BRIC stock indices reflect or increases volatility to a large extent by bad news. We confirmed earlier (EGARCH) and by present model that asymmetric effects is present in BRIC stock indices. One has to note that an asymmetric effect represents short term focus of investors. It suggests that investors are more attentive on their investment portfolio, they do not react as passionate and a kind of aggressive tendency to get their investment back as early even if they purchased for long term investment purpose.

CONCLUSIONS

Estimating stock market volatility is subject of interest not only for investors and researchers but it also reserves attention in general. Nowadays an advancement of econometric modeling provides such opportunities. This paper focuses on application of GARCH (1, 1), EGARCH and GJR-GARCH models. Investigation suggests that GARCH (1, 1) is fitted successfully for all BRIC economy markets. EGARCH and TGARCH has examined asymmetric effect of volatility clustering. The data covers period of ten years daily closing indices from BRIC economy markets. IBOVESPA, RTS, BSE SENSEX and SSE represents proxy from Brizil, Russia, India and China economy markets. We conclude that asymmetric GARCH class model gives improved elucidation of returns and volatility clustering than simple GARCH model. Nevertheless, an accurate calculation of any asymmetric GARCH class model provides better explanation of leverage effects. TGARCH and GJR-GARCH model estimates effects of good news and bad news on volatility. We employed GARCH class models with normal distribution (EGARCH and GJR-GARCH). Analysis of descriptive statistics provides negative skewness (long tail) and high kurtosis which represents magnitude of extreme or leptokurtosis effect for all BRIC economy stock indices. The changing pattern of volatility of Russia-RTS and India-SENSEX symbolize asymmetrical behavior. Nevertheless the change in China-SSE markets shows complete irregular pattern of movement, many researchers have identified it as gambling behavior. Volatility is most important factor of attraction, wise investment with calculated risk always generates good returns. We have focused this paper with objective to add value for understanding volatility clustering.

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