RETURNS AND VOLATILITY SPILLOVERS IN BRIC (BRAZIL, RUSSIA, INDIA, CHINA), EUROPE AND USA

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ABSTRACT

This paper studied the transmission of returns and volatility among six equity markets, four emerging (BRIC), US and Europe, using daily ETF data from February 3, 2012 to February 28, 2014. Multivariate Autoregressive Moving Average along with Generalized Autoregressive Conditional Heteroskedasticity are used to identify the source and magnitude of return and volatility spillovers. Our analysis indicates a significant co-movements among daily ETF returns, as well as significant volatility transmissions from the US and Europe to emerging markets. Among the BRICS only Russia and India exhibit a significant volatility spillovers from the United States but not from Europe.

INTRODUCTION

The growing global integration of financial markets has given rise to many studies that investigate the mechanism through which equity market movements are transmitted around the world. It is clear that real economic conditions and equity market performances are linked. However, the performance of equity markets also varies based on international factors. In fact, under some conditions, short-term equity performance may have less to do with expected fundamentals of individual countries than financial inflows (outflows). For example, starting in 2008, rounds of quantitative easing (QE) by the Federal Reserve (FED) in the US and the more recent actions by the European Central bank (ECB) resulted in near zero short term and very low long term interest rates. As investors look for higher returns countries like Brazil, Indonesia, India and Russia received capital flows from the US, Japan and Western Europe. Incoming financial flows have been mostly responsible for many emerging markets' spectacular performance after the 2008 up until the second half of 2013 (Morningstar 2014). In 2014 however, we observe reversing capital flows because the FED's announcement that the long term bond purchases would be eased and then stopped by the end of 2014. As a reaction, equity markets indices sank both in terms of local currencies as well as in dollar terms. The global financial cycle which started with FED (and ECB) policies of low interest rates resulted initially in capital flows into risky assets (high volatility) may have already run its course due to expected higher interest rates.

The intent in this paper is to explore return and volatility linkages among US, Europe and selected emerging markets (BRICS: Brazil, Russia, India, and China) by utilizing broad equity market index based Exchange Traded Funds (ETFs). The data period in this study (February 2012-February 2014) is appropriate since much of 2012 was rather calm but starting with the summer of 2013 many emerging markets have seen dips in their equity markets, sharp depreciation of their currencies and rising interest rates.

DATA

The present study uses data on country specific Exchange Traded Funds (ETF). The focus is on BRIC counties (Brazil, Russia, India and China), which are among the four largest emerging economies by either nominal or inflation adjusted GDP. We use the ETF data so that we can mitigate if not entirely some substantial problems that arise in traditional academic research such as exchange rates volatility, divergences in the national tax systems, diversities in stock exchange trading times and bank holidays, restrictions on cross-border trading and investments, transaction costs. We utilize daily data from February 3, 2012 to February 28, 2014, a sample of 519 days. The choice of the data period was based on the existence of the ETF data on all of the BRIC countries plus Europe-wide ETF and the S&P 500 ETF for the US (SPY). The ETFs that were used in this study are iShares MSCI ETFs: EWZ (Brazil), ERUS (Russia), INDA (India), MCHI (China), and IEV (Europe) and SPY (US)

METHODOLOGY

Multivariate Auto Regressive Moving Average (MARMA)

To study co-movements of daily returns, we utilized the Multivariate Autoregressive Moving Average (MARMA).

$$\varphi (L)Y_t = \omega(L) X_t + \theta(L) e_t \tag{1}$$

where $\varphi(L)$, $\omega(L)$, $\theta(L)$ are polynomials of different orders in L. Polynomial $\varphi(L)= (1 - \varphi_1 L^1 - \varphi_2 L^2 - \ldots - \varphi_p L^p)$ represents autoregressive part of order p, "L" denotes lag, and $L^1 Y_t$ represents $Y_{t-1,}$ and polynomial $\theta(L) =(1 - \theta_1 L^1 - \ldots - \theta_p L^q)$ represents moving average part of order q. For more on MARMA see [9]

Generalized Autoregressive Conditional Heteroskedasticity Model (GARCH)

To measure the dynamic relationship of the volatility of a process, among the models can be used are exponential smoothing or autoregressive conditional heteroskedastic (ARCH) and generalized autoregressive conditional heteroskedastic (GARCH) models. See [1] and [5]. GARCH models, have become widespread tools for dealing with time series heteroskedasticity and are more widely used to model the conditional volatility of financial series. In this study we use GARCH (1, 1) to analyze the persistence of conditional volatility of the returns as well as transmission of volatility of returns. Daily stock returns are calculated by 100* logarithmic difference of daily closing ETF values.

FINDINGS

ETF Returns

To fit an appropriate stochastic model, one has first to evaluate covariance, and cross correlations as well as the autocorrelations and partial correlations of data. The results of our investigation indicated that there are significant cross correlations of lag zero for most of the returns and cross correlations of lag one for some of the returns. Partial correlation and autocorrelation analysis indicated that only India demonstrated significant partial correlation of lag one. Consequently, MARMA model was used whereby for each return equation the regressors are the other five ETF returns, its own one-period lagged returns as well as one-period lagged returns of other ETF returns. Table 1 presents the co-movements of ETF returns.

Table 1- Co-movements of daily ETF Returns

$r_{t(Brazil)} = 0.245\, r_{t(Russia)} + 0.325\, r_{t(China)} + 0.114\, r_{t-1(India)} + 0.287 r_{t(Europe)} + 0.1044\, r_{t-1(US)} + e_t$
$r_{t(Russia)} = 0.276\, r_{t(Brazil)} + 0.085 r_{t(India)} + 0.182 r_{t(china)+}\, 0.539\, r_{t(US)} + 0.233 r_{t(Europe)} + 0.066\, r_{t-1(India)} + 0.236\, r_{t-1(Europe)} - 0.509\, r_{t-1(US)} + e_t$

$r_{t(India)} = 0.273r_{t(Brazil)} + 0.156r_{t(Russia)} + 0.258r_{t(china)} + 0.216r_{t-1(Europe\ )} - 0.129r_{t-1(India)} + e_t$
$r_{t(China)} = 0.305r_{t(Brazil)} + 0.168r_{t(Russia)} + 0.106\ r_{t-1\ (India)} + 0.429r_{t(us)} + e_t$
$r_{\ t(Europe)} = 0.122r_{t(Brazil)} + 0.088\ r_{t(Russia)} + 0.039_{t(India)} + 0.904\ r_{t(US)} + e_t$
$r_{t\ (US)} = 0.096r_{t\ (Russia)} + 0.436\ r_{t\ \ (Europe)} + 0.074r_{t-1\ (US)} - 0.028\ r_{t-1\ (India)} + 0.078r_{t(china)} + e_t$

Note: r and e represent returns and error terms

First, US market returns (ETF representing S&P 500) affect the returns in all of other sample countries except India. Second, most of the coefficients are positive indicating that the markets move together. The one exceptions is Russia where US return coefficient is negative, implying a negative correlation between the US returns and Russian returns. European returns also appear to be affected by returns from Brazil, Russia and the US. In short, the European and the US returns are quite similar in that first both have highest effect on the returns of each other, and they both are correlated with Russia's and India's returns. The differences include exclusion of Brazil in the US returns while Brazil is included in the European equation. Note also there is a positive co-movement among the returns of BRIC countries (table 1)

The findings of this analysis indicate that while interdependencies among the global stock markets have increased there are still very good opportunities for diversification. For example, US and Europe based investors may do well to ignore opportunities in each other's markets but can realize diversification benefits by investing in ETFs representing China.

ETF Volatilities:

In order to study the volatility and its persistency or transmission using a GARCH-type model it is a common practice to check the skewness and kurtosis of the error distributions of ARMA or regression and to test whether the distribution is normal. The results of the normality tests for the ETF return series indicated that most of the countries in sample have negative skewness (except Brazil and China). The kurtosis, or degree of excess, in all markets exceeds three, indicating a leptokurtic distribution. Accordingly, the Jarque-Bera test statistic (and corresponding *p*-value) rejects the null hypothesis of normal distribution for all returns in the sample at $\alpha=0.05$. Also, we noted that by looking at the standard deviations the highest volatility during the period of our study is exhibited by India (1.631) followed by Russia and Brazil and the ETF for US (0.76) has the lowest volatility. As expected, volatility is higher in emerging markets than in developed markets.

Volatility Persistence

Volatility persistence deals with the nature of volatility and whether the current period's volatility is affected by past periods' volatility. If volatility is "persistent," it implies that today's volatility arising out of new information today is likely to influence tomorrow's volatility and future volatilities. A study conducted by [8] on the Indian stock market found that volatility persisted for some time, and eventually, faded away. To analyze persistence in volatility, GARCH (1, 1) specification is commonly used. The sum of ARCH and GARCH coefficients is a measure of volatility persistence. If that sum is closer to one, it means that effects of shocks fade away very slowly.

As we mentioned above only returns of India demonstrated significant partial correlation of lag one. Thus, to study volatility persistence we fitted GARCH (1, 1) model to returns for all except returns of India.

Table 2--Volatility Persistence

coefficient	Brazil	Russia	India	China	Europe	US
constant	0.03 (0.260)	0.081 (0.073)	0.164 (0.031)	0.025 (0.279)	0.053 (0.052)	0.080 (0.036)
ARCH(-1) α	0.048 (0.028)	0.041 (0.024)	0.051 (0.009)		0.057 (0.0031)	0.009 (0.014)
GARCH(-1) β	0.938 (0.000)	0.924 (0.000)	0.886 (0.000)	0.984 (0.000)	0.898 (0.000)	0.771 (0.000)
α +β	0.986	0.965	0.937	0.984	0.956	0.865
AR(1)			-0.100 (0.031)			

The level of significance (α) is 0.10.

The parameters shown in the table lie within the expected range. The ARCH reaction parameter (α) usually ranges between 0.05 (for a market that is relatively stable) and about 0.1 (for a market that is jumpy). As shown in the table 3 the Arch coefficients are between 0.009 (US) and 0.057 (Europe) indicating stable short term volatility. Long term (cumulative) effects of past shocks on returns is measured by the Garch parameter, ß which usually ranges between 0.85 and 0.98. In this study, ß ranges from a low value of 0.771 in the US to 0.984 in China. Finally looking at both ARCH and GARCH effects together, Russia and China have α+ß values close1.0 indicating that the effects of the volatility shocks fade away slowly (Table 2).

Finally, table 3 below presents co-volatility of ETF returns. We estimated the co-volatility of returns (covariance of the standard deviations resulting from the Garch (1, 1) model).

Table 3- Co-Volatility of ETF's Returns[1]

	Cov(S_i &S_j)	P-Value		Cov(S_i&Sj)	P-value
(Brazil and Russia)	0.0299	0.000	(Russia and India)	0.0111	0.000
(Brazil and India)	0.0278	0.000	(Russia and China)	0.0035	0.000
(Brazil and China)	-0.0009	0.1331	(Russia and Europe)	0.0279	0.000
(Brazil and Europe)	0.0186	0.0000	(Russia and US)	0.0120	0.000
(Brazil and US)	0.0085	0.0000	(China and Europe)	0.0033	0.000
(India and China)	-0.0005	0.3872	(China and US)	-0.0002	0.371
(India and Europe)	0.0085	0.000	(Europe and US)	0.0113	0.000
(India and US)	0.0049	0.000			

The results given are conditional co-volatility of returns except for India.

Co-volatilities between, China and Brazil, China and India, China and US, were negative and statistically insignificant (see table 3). US's returns had the lowest co-volatility with India's returns

(0.004). Europe's returns had highest co-volatility with Russian returns (0.028). The above findings imply that the increase in market turbulence are associated with cross market volatility co-movements.

Volatility Transmission:

The transmission of shocks from the returns of one market to another was well-documented by [4]. Co-movements across volatilities (co-volatility) due to common information that simultaneously affects expectation in these markets and information spillovers caused by cross-market hedging are some of the reasons for volatility transmissions. In addition to endogenous events or variables, exogenous variables, that interest researchers to study volatility transmission.

To detect transmission of volatility between stock markets, we use the Augmented GARCH model as developed by [2].

Table 4- Volatility transmissions

$\sigma^2_{t(Brazil)} = 0.0306 + 0.048\, r^2_{t-1\,(Brazil)} + 0.939\, \sigma^2_{t-1(Brazil)}$
$\sigma^2_{t\,(Russia)} = 0.061 + 0.045\, r^2_{t-1\,(Russia)} + 0.956\sigma^2_{t-1\,(Russia)} - 0.109 r^2_{t-1\,(US)}$
$r_{t(India)} = -\,0.102\, r_{t-1(India)} + e_t$ $\sigma^2_{t\,(India)} = 0.089 + .037\, e^2_{t-1(India)} + 0.92\, \sigma^2_{t-1\,(India)} + 0.041\, r^2_{t-1\,(Russia)} - 0.125 r^2_{t-1\,(US)}$
$\sigma^2_{t(china)} = 0.025 + 0.984\, \sigma^2_{t-1(China)}$
$\sigma^2_{t(Europe)} = 0.03 + 0.964\sigma^2_{t-1\,(Europe)} + 0.027 r^2_{t-1\,(Russia)\,)} - 0.049 r^2_{t-1\,(US)} - 0.012\, r^2_{t-1\,(Brazil)}$
$\sigma^2_{t(US)} = 0.080 + 0.095 r^2_{t-1\,(US)} + 0.771\, \sigma^2_{t-1\,(US)}$

σ^2_t and r^2_t denote, respectively, variance and squared error

Among the BRIC countries, the markets not experiencing volatility spillovers from other markets are Brazil and China. Note also that Chinese market volatility is not transmitted to any other market. Russia and India on the other hand, exhibit volatility spillovers from the US. Note, however that the coefficient of the US volatility spillover term is negative implying that a drop in US market volatility increases volatilities in both Russian and Indian markets. There is evidence of cross-transmission of volatility among India and Russia stock markets (see table 4).

Volatility of the US market is unaffected by volatilities of the other markets. We may conclude that during the period covering this study (2012-2014) Volatility spillovers from the US and Europe to the emerging markets are not homogeneous across the BRIC markets. Many of the findings above provide partial support for some of the studies referred to in the literature review. e.g. [6], [10].

CONCLUSIONS

The findings of this study indicate that co-movements between daily ETF returns are significant. This finding points to decreasing opportunities for investors to diversify their portfolios. Nevertheless, we could still find significant diversification possibilities for investors.
We also found significant volatility transmissions from the US and Europe to emerging markets. However, these transmissions are not homogeneous across the BRIC markets. Among the BRICS only Russia and India exhibit a significant spillovers from the United States but not from Europe. Brazil and China do not have volatility transmission from other countries. These results are in line with findings of

other studies, such as [6], [7] that found significant return and volatility spillovers in India, Brazil and S. Africa.

In short, volatility transmission and the time-varying nature of volatility have implications for investors and portfolio managers who assess such information and rebalance their portfolios continually to achieve efficient portfolio diversification**.** The information is also important for policymakers in the sample countries for understanding the markets' co-movements and designing policies**.**

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