POSITIVE DEPENDENCE AND ASYMMETRY IN THE STOCK RETURNS OF THE TOP EMERGING ECONOMIES

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ABSTRACT

This research provides evidence of predictability and asymmetry in the stock return and volatility of the six future economic powers. Utilizing the fractionally integrated autoregressive moving average-fractional integrated general autoregressive conditional heteroskedasticity (ARFIMA-FIGARCH) models on daily returns of the major stock indices of Brazil, Russia, India, China, South Korea and Mexico, this research found that Brazil stock market returns has an intermediate memory, but long-run persistence is present in its volatilities as well as the stock market of China. The stock markets of Russia, India, Mexico and South Korea are non-stationary making simple autoregressive processes impossible in modeling them. The fractionally integrated autoregressive moving average-fractional integrated asymmetric power autoregressive conditional heteroskedasticity (ARFIMA-FIAPARCH) was also utilized to verify the initial results. The models confirmed that Brazil and China stock markets have long-memory properties. The models also showed that the stock market volatilities of Russia, India and South Korea have predictable structures. While India's stock exchange index exhibited dual long-memory properties in its returns and volatilities. On the other hand, the Mexican stock market maintained its non-stationary property under these set of models. This study also found that all of the top emerging countries showed strong evidences of volatility asymmetry, with negative news having bigger impact on stock return volatilities than positive news.

Keywords: long-memory and asymmetry, ARFIMA-FIGARCH/FIAPARCH models, stock returns and volatilities, top emerging economies

I. Introduction

One of the global economists of Goldman Sachs, Dr. Jim O'Neill, first coined the term BRIC (Brazil, Russia, India and China) in 2001 to refer to the four fastest growing economy in the world, making it a symbol of the shift in global economic power toward the developing market. A Goldman Sachs paper in 2003 predicts that by 2039, BRIC economies will be wealthier than the majority of the current major economic powers such as the G6 (Group of Six: France, Germany, Italy, Japan, UK and the US). Currently, BRIC nations compose over 25% of the world's land coverage, 40% of the world's population and almost $11 trillion dollars of combined GDP for 2010, making them the four economies in the emerging markets. With the wide acceptance of the BRIC countries, Dr. O'Neill posted two questions that will likely guide the economies' 2050 picture: 1) "Will the BRICs make it?" and 2) "Who else might join them?" Following the global economics paper of Goldman Sachs in 2005, they highlighted that South Korea and Mexico have the capability to become another major global economic player in the next couple of years. In fact, based on their predictions of 2025 largest economies, included in the Top 12 are these two countries. wherein. Figure 1 shows that included with the current advanced economies (G6 countries) are the emerging markets of BRICs plus South Korea and Mexico who even topped Brazil in the ranking.

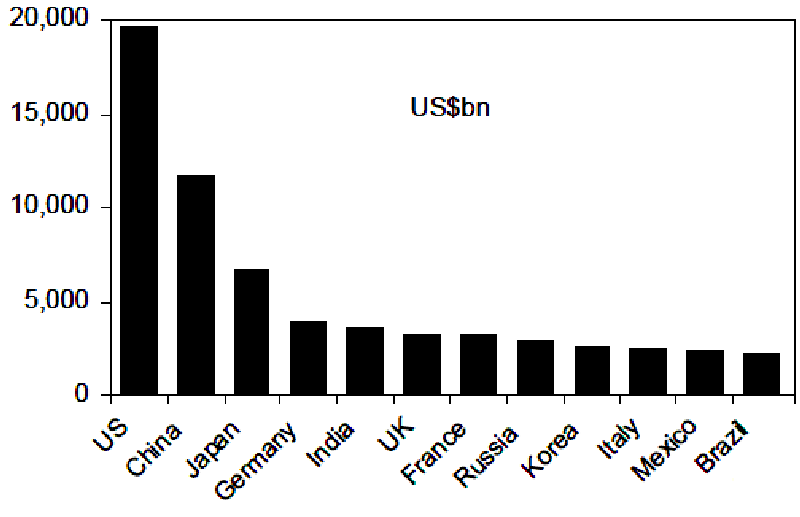

Figure 1: The Largest Economies of 2025
Source: Goldman Sachs Global Economic Paper No. 134 (2005)

These six economies have a commonality of having strong equity markets. Based on the Goldman Sachs' report, the BRICs' market capitalization could increase from $8 trillion to $25 trillion in 2020, and $59 trillion in 2030. These make BRIC markets have a 67.6% share of the total emerging equity markets capitalization for 2020 and a decade after, is projected to increase to 73.8% market share. The markets of South Korea and Mexico have the same scenario, wherein Korean Composite Stock Price Index (KOSPI) is experiencing a 12% growth, while Mexican Stock Exchange (BOLSA) posted a 10% increase in its market capitalization from 2011 up to the early first quarter of 2012. Based on the Goldman Sachs global economic report of 2010, emerging markets' equity capitalization could expand from $14 trillion to $37 trillion in 2020, and $80 trillion in 2030.

The possible prediction of the projected huge potential of emerging economies, particularly its equity market returns has long been a great interest for academicians and investors alike. However, the efficient market hypothesis (EMH) of Fama (1970) seems to always a viable explanation on the difficulty of predicting stock returns, especially of developed markets because it is believed that price movements occur accordingly in the market. However, a number of studies (Bekaert, 1995; Bekaert and Harvey, 1995; and Wright, 1999) have cited that emerging market returns have the tendency to be more persistent compared to more developed markets. These findings gave a great motivation for this study hoping that this could be a sign of market inefficiency and long memory properties could exists and possibly exploited by investors to earn excess returns. Another reason, according to Wright (1999) why emerging markets can be very attractive for portfolio diversification is their low correlation with developed markets and their obvious potential for profitability.

This research contributes to the literature on stock market returns by examining the long-memory properties of the hugely viable stock markets of Brazil, Russia, India, China, S outh Korea and Mexico. To investigate these hypotheses, this study utilizes the fractionally integrated autoregressive moving average (ARFIMA) processes first appeared in the papers of Granger and Joyeux (1980) and Hosking (1981), wherein the difference parameter is allowed to be a non-integer; the fractional integrated general autoregressive conditional heteroskedasticity (FIGARCH) and fractional integrated asymmetric power autoregressive conditional heteroskedasticity (FIAPARCH) model to verify long memory and asymmetry in stock return volatility as suggested by Baillie et al. (1996).

The closest literature to this study is the one written by Wright (1999) regarding emerging markets wherein Brazil and India were included in the samples. The author was able to prove the presence of long-memory in emerging markets in general. A study of Ural and Kucukozmen (2011) also provided evidences on the dual long-memory properties of stock returns of advanced countries and found that both returns and volatilities have predictable structure and markets are weak form efficient in general. To the best of our knowledge no formal empirical literature yet has study the long-memory properties of the major stock index returns of the biggest emerging economies using ARFIMA-FIGARCH and ARFIMA-FIAPARCH models.

The presence of a long-memory in stock returns can shaken the EMH, because it means that lagged returns can be utilized to make predictions on future returns. The literature of ARFIMA-FIGARCH models have been proven to capture long-memory properties of time-series data. The studies of Floros, et al. (2007), Kang and Yoon (2007), McMillan and Thupayagale (2008) and Korkmaz et al. (2009) utilized the models to study stock market returns, Beine et al. (2002) and Nouira et al. (2004) used it to model exchange rates and Choi and Hammoudeh (2009) utilized it for commodities. On the other hand, the studies on the ARFIMA-FIAPARCH models did not only capture long-memory properties in return and volatilities but also able to provided strong evidences of volatility asymmetry by looking at the APARCH delta (δ) parameter. The literature of Mabrouk and Aloui (2010), Tan and Khan (2010) and Wiphtthananthakul and Sriboonchitta (2010) provided empirical proofs when they studied the stock market returns of Tunisia, Malaysia and Thailand, respectively.

This paper aims to first, examine the long-memory properties in the returns and volatilities of Brazil's Bovespa Stock Index (BVSP), Russia's Trading System Index (RTS), India's Bombay Stock Exchange Index (BSE), China's Shanghai Stock Exchange Composite Index (SSE), Korea's KOSPI and Mexico's BOLSA; second, put to test the EMH, suggesting that returns have a random walk of Fama (1970); third, look if there exists a dual long memory in returns and volatilities in the stock markets of emerging economies, like what Kang and Yoon (2007) discovered for Korean stock returns; and lastly, find evidences of asymmetric volatility properties in stock returns related to the earlier findings of Mabrouk and Aloui (2010), and Tan and Khan (2010) in Tunisian and Malaysian markets, respectively

The research is written as follows. Section 2 explains the data and ARFIMA-FIGARCH models; Section 3 presents the empirical results; and Section IV presents the conclusion.

2. Data and Methodology

Daily closing prices of the top emerging markets stock returns of BVSP, RTS, BSE, SSE, KOSPI and BOLSA during the last decade beginning at December 2001 until December 2011 were obtained from the Yahoo Finance Web site with an average observation of 2,471 returns. The data was limited to the last decade because top emerging nations gained their strong economic momentum during this era. The data were modeled by ARFIMA-

FIGARCH and ARFIMA-FIAPARCH processes and are explained below.

2.1 The fractionally integrated autoregressive moving average (ARFIMA) model

Based on Granger and Joyeux (1980) and Hosking (1981), the ARFIMA model is a parametric approach used to examine long-memory properties of time-series. A unique characteristic of the model is that it allows the difference parameter to be a non-integer and consider the fractionally integrated process $I(d)$ in the conditional mean. The ARFIMA (p, d, q) model satisfies both stationarity and invariability conditions and can be expressed as:

$$\phi(L)(1-L)^{d}(X_t-\mu)=\theta(L)\varepsilon_t, \tag{1}$$

$$\varepsilon_t = z_{t\sigma_t}, \qquad z_t \sim N(0.1), \tag{2}$$

where $\phi(L)=1-\phi_1 L-\phi_2 L^2-\ldots-\phi_P L^P$ and $\theta(L)=1-\theta_1 L-\theta_2 L^2-\ldots-\theta_P L^P$ are the autoregressive (AR) and moving average (MA) assumed to have all roots outside the unit circle, ***d*** is a fractional integration real number parameter, L is the lag operator and ε_t is a white noise residual. The $(1-L)^d$ is the fractional differencing lag operator.

The process is called stationary when the ARFIMA model is $-0.5 < d < 0.5$. This is where the effect of shocks to ε_t decays at a gradual rate to zero. Also, the process has a short memory if $d = 0$. This is where the effect of shocks decays geometrically. A unit root process is exhibited when $d = 1$. A long memory process or the so-called positive dependence among remote observations exists when $0 < d < 0.5$. On the other hand, there is a presence of intermediate memory or antipersistence when $-0.5 < d < 0$ (Baillie, 1996). The process is non-stationary if $d \geq 0.5$, while it is stationary but noninvertible process if $d \leq -0.5$, making the time-series impossible to model by any autoregressive process.

2.2 The fractional integrated general autoregressive conditional heteroskedasticity (FIGARCH) model

As proposed by Baillie et al. (1996), the FIGARCH model extends the traditional GARCH model to consider fractional integration which allows the distinguishing parameter ***d*** to be a non-integer. The model captures short, intermediate and long memory in return volatility of econometric time-series. The FIGARCH (p, d, q) model can be written as:

$$\left[\phi(L)(1-L)^{d}\right]\varepsilon_t^2=\omega+[1-\beta(L)](\varepsilon_t^2-\sigma_t^2), \tag{3}$$

where *(L)* is the lag-operator, $\lambda\ (L) = \sum_{i=1}^{\infty} \lambda_i L^i$ and **0** ≤ *d* ≤ **1**. λ *(L)* is an infinite summation which, in practice, has to be truncated. $(1 - L)^d$ is the fractional differencing operator.

2.3 The fractional integrated asymmetric power autoregressive conditional heteroskedasticity (FIAPARCH) model

As shown by Tse (1998), the FIGARCH (*p, d, q*) process is further extended in order to capture asymmetry aside from the long memory feature in the conditional variance through the FIAPARCH model. Through this, the FIAPARCH (*p, d, q*) model is seen to be superior than the FIGARCH process. FIAPARCH introduced the function $\left(\left|\varepsilon_t\right| - \gamma\varepsilon_t\right)^\delta$ and can be expressed as follows:

$$\sigma_t^\delta = \omega\left[1 - \beta(L)\right]^{-1} + \left\{1 - \left[1 - \beta(L)\right]^{-1}\rho(L)(1 - L)^d\right\}\left(\left|\varepsilon_t\right| - \gamma\varepsilon_t\right)^\delta, \quad (4)$$

where δ, γ and λ and the model parameters. The differencing parameter *d* dictates the long-memory property of the volatility if **0** ‹ *d* ‹ **1**; negative shocks have relatively more impact than positive shocks on volatility if γ › **0**, and the inverse is also the same; λ serves as the power term in the volatility structure. The FIAPARCH process can be also reduced to the FIGARCH model if γ = **0** and δ = 2.

3. Empirical Results

Table 1 shows that the average stock returns of the emerging economies experienced gains during the past decade. RTSI has the highest average positive returns posted with 7.7%, while SSEI has the lowest with an average of 1.3%. RTSI again posted the highest volatility among the major stock indices with a 2.27 standard deviation and this may be an evidence of the Modern Portfolio Theory of Markowitz (1952) that the greater dispersion of returns, the higher the risk of an investment which may lead to higher gains and higher losses. Most of the samples are negatively skewed and the kurtosis coefficients have leptokurtic distributions. The Jarque-Bera statistic for residual normality illustrates that the stock returns of the emerging economies are under a non-normal distribution assumption. Table 2 illustrates the initial filtering done by the study. The Augmented Dickey-Fuller (ADF) test established the stationarity of the data to eliminate serial correlation and heteroscedasticity in the data. The minimum value of the Akaike Information Criterion (AIC) is utilized to identify the orders of the models. All stock return samples have no serial correlation, based on the results of the Lagrange Multiplier (LM) test. This paper used the ARCH-LM process to test the ARCH effect and shows that we can apply GARCH models in the chosen sample, because the null hypothesis was rejected for all the data sets.

Table 3 features the results for both ARFIMA-FIGARCH and ARFIMA-FIAPARCH models. Intermediate memory was found in the returns of Brazil stock market. This means that persistency in having positive or negative returns in a particular time are weak and may be changing its course soon. However, the antipersistence on the returns of Brazil is compensated by the persistence in its volatilities. Long-memory properties have been detected from the stock market volatilities of Brazil and China. The predictable structures in volatility of the two big markets may be a clear sign of market inefficiency and investors may earn excess returns, because positive dependence was seen in their volatility structures. These results are consistent with the studies of Kang and Yoon (2007), Korkmaz et al. (2009), and Tan and Khan (2010) in studying the South Korean, Turkish and Malaysian stock markets, respectively. The remaining economies of Russia, India, Mexico and South Korea are characterized by non-stationarity and autoregressive process may find difficulty in modeling them. To confirm these findings, the ARFIMA-FIAPARCH models did not just verify that Brazil and China stock markets have long-memory properties, but the models also pointed out that the stock market volatilities of Russia, India and South Korea exhibits positive dependence and also have predictable structures. India's stock exchange index SENSEX does not only have long-memory in its volatilities, but also exhibit positive dependence in its returns. These findings are again in-line with the findings of Kang and Yoon (2007), Korkmaz et al. (2009), and Tan and Khan (2010) in finding long-memory properties in stock market volatilities. The dual long-memory process found in India and the long-memory process in the volatility of South Korean stock exchange KOSPI are also consistent with the study of Kang and Yoon (2010) in their dual long-memory characterizations of two South Korea stock markets, KOSPI and Korea Securities Dealers Automated Quotation (KOSDAQ). The Mexican stock market maintained its nonstationary property under the ARFIMA-FIAPARCH models. These differences in the results of the two models utilized made the paper looked at their log-likelihood values. The study found out that ARFIMA-FIAPARCH models provided the best representation of the conditional mean and variance dynamics and is the better combination of models to characterize return volatilities of these soon-to-be advanced economies.

This research also discovered that all of the countries under study displayed strong evidences of volatility asymmetry by looking at the APARCH delta (δ) parameters wherein the values are all positive and significant at the 1% level of significance. These findings find support from the studies of Mabrouk and Aloui (2010) Tan and Khan (2010) and Wiphtthananthakul and Sriboonchitta (2010) when they studied the stock market returns of Tunisia, Malaysia and Thailand, respectively. Furthermore, the gamma (γ) coefficients of asymmetric volatility response to news for all countries are also significant at the same level. This paper found that negative news has bigger impact on stock return volatilities than positive news of the same magnitude. This is not a surprise for the vast majority of literatures since bad news typically creates heightened emotions of panic and fear resulting to larger movements in returns that typically creates losses. These results are consistent with the earlier studies of Mabrouk and Aloui (2010) and Tan and Khan (2010), wherein they found out that good news have relatively smaller impacts on the stock returns of Tunisian and Malaysian markets, respectively. Among the economies under study, Mexico and South Korean stock markets posted the highest asymmetry and China stock market has the lowest. This paper hypothesizes that the increasingly dominant status of the Chinese stock market is being viewed in having more stability in the economy and investments, while the relatively small stock markets of Mexico and South Korea are being viewed to be still riskier and comparatively unstable.

4. Conclusion

Predicting stock returns and volatilities of top emerging economies have long been a great interest because of their relatively huge potential for upside swings. This research answered this question by providing evidences in stock return and volatility predictability of the six future economic powers. Utilizing the ARFIMA-FIGARCH models on daily returns of the major stock indices of Brazil, Russia, India, China, South Korea and Mexico, this research found that Brazil stock market returns has an intermediate memory, which means that persistency is weak and may be changing its course sooner than expected. However, the persistence is present in its volatilities as well as the stock market of China. The predictability in volatility of the two big markets is a clear sign of market inefficiency and investors may earn excess returns by observing their volatilities. The stock markets of Russia, India, Mexico and South Korea are non-stationary making simple autoregressive processes impossible in modeling them.

To verify the results of the first set of models, the ARFIMA-FIAPARCH was also utilized. The models confirmed that Brazil and China stock markets have long-memory properties. The models also showed that the stock market volatilities of Russia, India and South Korea have predictable structures. While India's stock exchange index exhibited dual long-memory properties in its returns and volatilities. Investors can expect to have abnormal returns in the Bombay stock exchange given proper modeling and forecasting tools. On the other hand, the Mexican stock market maintained its nonstationary property under these set of models.

A unique feature of the ARFIMA-FIAPARCH models is their ability to determine volatility asymmetry through its delta (δ) parameter. This study found that all of the top emerging countries showed strong evidences of volatility asymmetry, showing that negative news has bigger impact on stock return volatilities than positive news of the same magnitude. Mexico and South Korean stock markets exhibited the highest asymmetries while China stock market has the lowest. This can be attributed to the increasingly dominant status of the Chinese stock market in the past decade wherein the country is viewed to be more stable compared to Mexico and South Korea which can be perceived as relatively riskier markets.

Table 1: The Sample Size and Period of BRIC stock returns

Top Emerging Stock Indices	Start of Data	Obs.	Mean	Std. Dev.	Skew.	Kurt.	J-Bera
Brazilian Bovespa Index (BVSP)	Dec. 4, 2001	2468	0.060	1.920	-0.119	7.416	2010.771***
Russian Trading System Index (RTSI)	Dec. 4, 2001	2485	0.077	2.269	-0.510	13.573	11682.750***
Bombay Stock Exchange Index (SENSEX)	Dec. 4, 2001	2476	0.065	1.649	-0.068	10.599	5958.747***
Shanghai Stock Exchange Index (SSEI)	Dec. 4, 2001	2414	0.013	1.725	-0.171	6.433	1197.227***
Mexico Stock Exchange Index (BMV)	Dec. 4, 2001	2512	0.073	1.386	0.050	8.051	2671.039***
South Korean Stock Exchange Index (KOSPI)	Dec. 4, 2001	2471	0.044	1.616	-0.438	7.371	2046.195***

Source: Yahoo Finance – December 2001 to December 2011; http://www.yahoo.com/finance.

Table 2: Summary Statistics of ARMA and GARCH filtering

Stock Returns	ADF	ARMA	d-coeff.	AIC	LM test	ARCH-LM	GARCH	AIC	ARCH-LM
Brazil BVSP	-31.189***	(1,2)	0.107 (0.170)	4.142	1.506	233.442***	(2,2)	3.921	0.615
Russia RTSI	-22.112***	(2,2)	0.025 (0.194)	4.461	0.565	163.916***	(1,2)	4.055	0.006
India SENSEX	-35.683***	(2,0)	0.015 (0.603)	3.835	0.005	67.150***	(1,1)	3.493	0.069
China SSEI	-22.806***	(2,2)	0.028 (0.065)*	3.924	0.234	22.925***	(2,2)	3.732	0.063
Mexico BMV	-30.092***	(0,1)	-0.050 (0.019)**	3.485	0.770	90.251***	(2,2)	3.204	1.007
S. Korea KOSPI	-48.276***	(1,1)	-0.032 (0.479)	3.800	0.158	98.309***	(1,2)	3.523	0.189

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 3: Summary Statistics of ARFIMA-FIGARCH and ARFIMA-FIAPARCH models

BRIC	ARFIMA-FIGARCH				ARFIMA-FIAPARCH					
Stock Indices	d-coeff.	ARCH	d-coeff.	AIC	d-coeff.	ARCH	d-coeff.	delta	gamma	AIC
Brazil BVSP	-0.047* (0.090)	(1,0)	0.411*** (0.000)	3.922	-0.002 (0.950)	(1,2)	0.412*** (0.000)	1.185*** (0.000)	0.730*** (0.002)	3.903
Russia RTSI	-0.007 (0.803)	(1,0)	0.522*** (0.000)	4.058	0.013 (0.669)	(2,1)	0.395*** (0.000)	1.458*** (0.000)	0.338*** (0.001)	4.046
India SENSEX	0.012 (0.739)	(1,2)	0.568*** (0.000)	3.491	0.097** (0.020)	(0,2)	0.385*** (0.000)	1.447*** (0.000)	0.534*** (0.000)	3.467
China SSEI	0.033 (0.191)	(2,2)	0.496*** (0.000)	3.730	0.036 (0.167)	(0,2)	0.348*** (0.000)	1.665*** (0.000)	0.204** (0.022)	3.734
Mexico	-0.030 (0.218)	(2,2)	0.535*** (0.000)	3.204	0.016 (0.537)	(1,2)	0.534*** (0.000)	1.165*** (0.000)	0.854*** (0.000)	3.165
S. Korea KOSPI	-0.054 (0.220)	(1,2)	0.583*** (0.000)	3.526	0.036 (0.135)	(2,1)	0.374*** (0.000)	1.304*** (0.000)	0.857*** (0.007)	3.502

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

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