ARE FRONTIER STOCK MARKETS MORE INEFFICIENT THAN EMERGING STOCK MARKETS?

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ABSTRACT

This paper investigates the presence of long memory in MSCI's Frontier and Emerging Market Indices, using ARFIMA and FIGARCH models. The concept of "long memory" has become important recently in financial academic research. Our data set consists of daily returns computed from indices of frontier and emerging markets. Long memory tests are carried out both for the returns and volatilities of these series. Results of the ARFIMA models indicate the existence of long memory in Frontier markets return series. Presence of long memory properties in return series is indicative of inefficiency or efficiency in stock markets, and therefore, are useful to investors interested in diversifying their portfolios.

1. INTRODUCTION

In recent years, long memory properties of stock returns have been heavily investigated to determine if stock markets are "efficient" or not. When "long memory" is present in returns and volatility, it implies that there exist dependencies between distant observations. In other words, long memory in return series is linked with a high autocorrelation function, which decays hyperbolically, and dies out as time passes. In contrast, if distant observations have very low correlations, the series is said to show short memory, and it is known to have exponentially decaying correlations. Consequently, the autocorrelation function for an I(0) process shows an exponential decay, and it shows an infinite persistence for an I(1) process.

There have been numerous studies on the use of long memory in time series. For example, Granger and Joyeux [16] and Hosking [18] showed that fractionally integrated series could produce long memory property, and proposed the fractionally integrated autoregressive moving average (ARFIMA) model. The ARFIMA model or the fractionally integrated process, I(d), is characterized by the autocorrelation function, which decays at a hyperbolic rate. In stock market research, presence of the long memory in returns has been investigated extensively using the ARFIMA model. Results of empirical studies in this area have not been conclusive. For example, Lo [23], Crato [11]), Cheung and Lai [10], Barkoulas and Baum [[4], Jacobsen [19] and Tolvi [29] found no long memory characteristics in daily stock returns of developed stock markets. Evidence of long memory, however, was found in results of Sadique and Silvapulle [27], Henry [17] and Gil-Alana [15].

Long memory in volatility of stock returns has also been studied intensively. Ding et al. [12] found that there was slow decay in autocorrelation coefficients of the squared daily stock returns. This study led other researchers to investigate this issue further (see, for example, Li [21], Vilasuso [30], Andersen et al. [1], Pong et al. [26], Martens and Zein [24], Martens et al. [25], and Bhardwaj and Norman [6]). Baillie et al. [3] proposed the fractionally integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) model by generalizing the IGARCH model to allow for persistence in the conditional variance, and provided a useful model for series in which the conditional variance is persistent.

"Long memory" is said to be present in asset returns if the market does not immediately respond to new information. In such cases, markets react to new information gradually over time. Since the returns series are not independent over time, past asset returns could be used to predict future returns. There is a strong possibility of making consistent speculative profits if long memory property is discovered in asset returns. This is in contradiction to the weak form market efficiency hypothesis, which states that past returns cannot predict future returns. Long memory has also been studied in a recent paper on dollar-yen exchange rates (Caporale and Gil-Alana [8]).

Despite the vast literature that examines the long memory properties of major stock market prices, relatively little research has been done on the time series properties of returns and volatilities in emerging markets and frontier markets. It is very likely that long memory will be detected in emerging & frontier markets since they do not always behave as expected, and the efficient market hypothesis may not necessarily hold for stock returns in small markets. To verify this, Barkoulas et al. [5] investigated the presence of long memory in the Greek stock market, and find strong evidence of it. Wright [31] also investigated several emerging stock markets, and found that small markets tend to have long memory more often than in major markets. Since global investors consider emerging and frontier stock markets to be an important source for global portfolio diversification, an understanding of the dynamic behavior of stock returns in these countries is crucial. The primary objective of this paper is to investigate the long memory property in the asset returns and volatility of frontier and emerging markets, as proxied by MSCI frontier and emerging market indices.

Many of the frontier and emerging markets have undergone major changes in their economic and political systems during the last decade. Remarkable developments in terms of market capitalization and daily trading volumes continue to occur in these small markets, despite concerns about low liquidity and high volatility. These stock markets appear to be well integrated with world financial markets due to removal of restrictions on portfolio capital movements. However, their sensitivity to shifts in regional and worldwide portfolio adjustments of large investment funds may be very high due to their small size compared to the stock exchanges of developed markets. As a result, these markets may be more volatile than well-established stock markets.

An important empirical question in this context is to ask whether or not the stock returns and volatility in emerging and frontier stock market indices have long memory properties. To answer this question, this study employs autoregressive fractionally integrated moving average (ARFIMA), and fractionally integrated GARCH (FIGARCH) models. These models help us analyze the relationship between conditional mean and conditional variance of a process showing the long memory property, (see Kang and Yoon, [20]). In addition, these models provide a greater flexibility to analyze long memory in the returns and volatility with the fractionally differencing process.

The rest of the paper is organized as follows: The methodology is presented in Section 2. Section 3 gives information about the data and reports the empirical results. Section 4 is devoted to conclusions.

2. METHODOLOGY

To investigate long memory in our frontier and emerging stock market returns and volatilities, we use ARFIMA, GARCH, and FIGARCH models.

2.1. ARFIMA model

Granger and Joyeux [16] and Hosking [18] were the pioneers behind the ARFIMA. That model became a popular parametric approach to test long memory property in asset returns. Denoting L as the lag operator and replacing the difference operator (1−L) of an ARIMA process with the fractional difference operator $(1-L)^{\xi}$, where ξ denotes the degree of fractional integration, they define the so-called Autoregressive Fractionally Integrated Moving Average (ARFIMA) process. For the observed series y_t t=1,..., T, the ARFIMA (p, ξ, q) process can be expressed as:

$$\Psi(L)(1-L)^{\xi}(y_t-\mu)=\Theta(L)\varepsilon_t \tag{1}$$

$$\varepsilon_t=z_t\sigma_t, \quad z_t\sim N(0,1) \tag{2}$$

where μ is the unconditional mean and ε_t is independently and identically distributed (i.i.d.) error term. $\Psi(L)=1-\psi_1L-\psi_2L^2-...-\psi_pL^p$ and $\Theta(L)=1+\theta_1L+\theta_2L^2+...+\theta_qL^q$ are the typical AR and MA lag polynomials. Long range properties of any series depend on the value of ξ. For $\xi\in(0, 0.5)$, the autocorrelations are all positive. They decay hyperbolically to zero as lag length increases, compared to the usual exponential decay in the case of stationary ARMA model with ξ=0. For $\xi\in(-0.5, 0)$, the series is said to exhibit intermediate memory. In this case the autocorrelations are all negative, and decay hyperbolically to zero. For $\xi\in(-0.5, 0.5)$, the series is stationary and invertible. However, for ξ=1, the series follows a unit root process.

2.2. GARCH model

The traditional GARCH (p, q) model developed by Bollerslev [7] can be written as follows:

$$\begin{aligned} r_t &= \mu+\varepsilon_t \\ \sigma_t^2 &= \omega+\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2+\sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \\ &= \omega+\alpha(L)\varepsilon_t^2+\beta(L)\sigma_t^2 \end{aligned} \tag{3}$$

Where r_t is the daily return, σ^2_t is the conditional variance ($\omega>0$, $\alpha_i\geq0$, $\beta_j\geq0$, $\forall_i$, $\forall_j$), α(L) and β(L) are the lag polynomials of order q and p. One can derive from Eq. (3) the following expression:

$$[1-\alpha(L)-\beta(L)]\varepsilon_t^2=\omega+[1-\beta(L)]v_t \tag{4}$$

where $v_t=\varepsilon_t^2-\sigma_t^2$. The GARCH (p, q) model is covariance stationary if all the roots of 1−α(L)−β(L) lie outside the unit circle. When the lag polynomial 1−α(L)−β(L) contains a unit root, the GARCH (p, q) process becomes an integrated GARCH process, denoted as IGARCH (p, q). Engle and Bollerslev [13] defined the IGARCH (p, q):

$$\phi(L)[1-L]\varepsilon_t^2=\omega+[1-\beta(L)]v_t \tag{5}$$

where $\varphi(L)=[1-\alpha(L)-\beta(L)](1-L)^{-1}$. The main drawback of this model is that shocks to the conditional variance are completely persistent, and the unconditional variance does not exist. Although the GARCH model is flexible, and has numerous extensions to include particular characteristics of financial markets, such as asymmetry, switching regime and news impact, it is not able to adequately explain the various findings of persistence or long memory in the volatility of financial returns series.

2.3. FIGARCH model

Similar research on the volatility (see Baillie et al., [3] has led to an extension of the ARFIMA representation in ε^2_t, leading to the Fractionally Integrated GARCH (FIGARCH) model. Baillie et al. [3] introduced the FIGARCH process to recover the long memory observed in the volatility of financial return series. In contrast to an I(0) time series in which shocks die out at an exponential rate, or an I(1) time series in which there is no mean reversion, shocks to an I(d) time series with 0<d<1 decay at a very slow hyperbolic rate. The FIGARCH (p, d, q) model is given by

$$\varphi(L)(1-L)^d \epsilon^2_t = \omega + [1-\beta(L)]v_t \qquad (6)$$

It is assumed that all the roots of $\varphi(L)$ and $[1-\beta(L)]$ lie outside the unit circle. FIGARCH model nests GARCH and IGARCH model. If d=0, the FIGARCH (p, d, q) process reduces to a GARCH (p, q) process and if d=1, the FIGARCH process becomes an integrated GARCH process. Rearranging the terms in Eq. (5), one can write the FIGARCH model as follows:

$$[1-\beta(L)]\sigma^2_t = \omega + [1-\beta(L)-\varphi(L)(1-L)^d]\epsilon^2_t \qquad (7)$$

The conditional variance of ε^2_t is obtained by:

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

That is:

$$\sigma_t^2 = \frac{\omega}{[1-\beta(1)]} + \lambda(L)\varepsilon_t^2 \qquad (8)$$

where $\lambda(L)=\lambda_1 L+\lambda_2 L^2$... Baillie et al. [3] state that the impact of a shock on the conditional variance of FIGARCH (p, d, q) processes decrease at a hyperbolic rate when $0\leq d<1$. Hence, the long-term dynamics of the volatility is taken into account by the fractional integration parameter d, and the short-term dynamics is modeled through the traditional GARCH parameters.

A conventional model selection criterion, the Akaike's information Criterion (AIC), is used to choose the best model that describes the data. Hence ARFIMA (1, ξ,0) and ARFIMA(0, ξ,2) are chosen for emerging markets (hereafter, EM) and frontier markets (FM), respectively. Since long memory parameter is not significant for EM, ARMA(1,0) is chosen based on AIC for EM.

3. DATA AND EMPIRICAL RESULTS

3.1. Data

Our data set consists of the daily index levels of MSCI Emerging Market Index and MSCI Frontier Market Index from Nov 27, 2008 to November 26, 2012. We are restricted by data availability on those two indices, hence, the focus is on that time period. Information about countries covered in each of these indices is provided in detail in the Appendix.

Daily stock returns are calculated by taking the logarithmic difference of daily closing index values. Descriptive statistics for these two indices are reported in Table 1. All return series reveal that they do not correspond with the normal distribution assumption. We can conclude that there are significant departures from normality by looking at the Jarque–Bera (JB) statistics. In addition, the two series are negatively skewed and leptokurtic. In order to test the hypothesis of independence, Ljung–Box statistics is estimated for the returns and squared returns, and presented in Table 1. From these test statistics, we certainly can reject the null of white noise and assert that these return series are autocorrelated.

[INSERT TABLE 1 HERE]

3.2. Empirical results

First, we test for stochastic trends in the autoregressive representation of each individual return series using a unit root test. We find that stock market indices of frontier and emerging markets have unit roots, are non-stationary in levels, but the return series are themselves stationary. Unit root test results are not provided here but can be made available upon request. We then test for long memory in stock returns and volatility.

3.3. Long memory in returns

Estimation results and diagnostic statistics of ARFIMA (p, ξ, q) models are reported in Table 2.

[INSERT TABLE 2 HERE]

We estimated different specifications of the ARMA (p, ξ, q) with $p+q \leq 2$ for each return series, based on Cheung [9]. A conventional model selection criterion, the Akaike's information Criterion (AIC), is used to choose the best model that describes the data. Preferred models for each series are reported in the top row of Table 2. Our results indicate that the long memory parameter (ξ) are significantly different from zero for index return series in frontier markets. We conclude that ARFIMA models support the evidence of long memory only in frontier markets return series. Since long memory in returns implies that stock prices follow a predictable behavior, which is inconsistent with the efficient market hypothesis, to this end, only emerging stock markets can be attributed to be possessing efficiency. These results are in line with the findings of recent studies, which claim that long memory property is generally a characteristic of developing rather than developed stock markets (see, for example, Barkoulas et al., [5]; Sourial, [28]; Limam, [22]; Assaf, [2]; Kang and Yoon, [20]; Floros et al., [14]).

Diagnostic statistics in Table 1, however, suggest that the standardized residuals display skewness and excess kurtosis. Residuals are mostly negatively skewed, implying that the distribution is non-symmetric. In addition, the large value of kurtosis statistics suggests that residuals appear to be leptokurtic, or fat-tailed, and sharply peaked about the mean when compared with normal distribution. The large values of the Jarque–Bera (JB) statistic also imply a deviation from normality. Moreover, the ARCH statistics are highly significant, indicating the existence of ARCH effects in the standardized residuals. The significant Q-statistics indicate that the residuals are not independent. These diagnostic statistics suggest that the residuals distribution of the ARFIMA models considered in this study is not white-noise. Modeling only the level of returns does not provide a clear picture on the presence of long memory property in the frontier and emerging stock markets. Consequently, we need to investigate the presence of long memory in volatility.

3.4. Long memory in returns and volatility

It is important to investigate the dual long memory property in both the conditional mean and conditional variance, since long memory dynamics are commonly observed in both of them. For our emerging and frontier stock market indices, the models with different orders are estimated for ARFIMA–GARCH, and ARFIMA–FIGARCH models. Model selection is based on AIC and Ljung–Box Q-statistics. The model which has the lowest AIC, and passes Q-test simultaneously, is used. Estimates of ARFIMA–GARCH, and ARFIMA–FIGARCH models under the normal, student's t and skewed t distributions were calculated. Significant student-t distribution parameter (v) and insignificant skewed student-t disttirbution suggested the use of student-t distibution. Consequently, only student-t distribution results are shown in Table 3.

[INSERT TABLE 3 HERE]

Based on our test results from Table 3, we can infer that FIGARCH must be used instead of GARCH because FIGARCH parameters are statistically significant. Note that sum of alpha+beta measures the persistency in conditional volatility. FIGARCH gives the more realistic and lower persistency, which is crucial for financial modelling. As seen in the tables, according to the AIC, the FIGARCH models fit the return series better than the GARCH models.

3.5. Forecasting performance

To assess the performance of the GARCH models in forecasting the conditional variance, we use mean squared error (MSE), and mean absolute error (MAE). These measures are computed as follows:

$$\text{MSE} = \frac{1}{h+1}\sum_{t=s}^{s+h}\left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2 \tag{9}$$

$$\text{MAE} = \frac{1}{h+1}\sum_{t=s}^{s+h}\left|\hat{\sigma}_t^2 - \sigma_t^2\right| \tag{10}$$

where h is the number of steps ahead, in this paper *h* is equal to 1 (one-step ahead forecasting), *s* is the sample size, $\hat{\sigma}_t^2$ is the forecasted variance, and σ_t^2 is the actual variance. Tables 4 and 5 provide results of these two measures.

[INSERT TABLE 4 HERE]
[INSERT TABLE 5 HERE]

The winner is the ARFIMA–FIGARCH model in terms of MSE and MAE. Hence, for out-of-sample forecasting, the comparison between models strongly supports the use of long memory volatility models.

(AUTHORS' CONCLUSIONS, APPENDIX, REFERENCES ARE AVAILABLE FROM THE AUTHORS (PDHEERIYA@CSUDH.EDU UPON REQUEST)