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ARFIMA-FIGARCH VS. ARFIMA-HYGARCH: CASE STUDY ETF RETURNS OF EMERGING ASIAN COUNTRIES

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ABSTRACT

This research investigate the long memory returns for ETF returns index of seven Asian countries in Emerging Markets Equities during 2008-2013 periods. Those ETFs are Wisdom Tree Indian Rupee Fund (ICN), Market Vectors Indonesia Index (IDX), iShares MSCI Malaysia Index Fund (EWM), Market Vectors Russia ETF (RSX), and iShares MSCI Thailand Investable Market Index Fund (THD), SPDR S&P China ETF (GXC), and Market Vectors Vietnam ETF (VNM). The ARFIMA, ARFIMA-FIGARCH, and ARFIMA-HYGARCH models were estimated. The empirical results of log-likelihood information criterion analyses, the statistics supports ARFIMA-HYGARCH model instead of ARFIMA and ARFIMA-FIGARCH models.

Keywords: Asian emerging markets, currency ETF, EGARCH, ARFIMA-FIGARCH, ARFIMA-HYGARCH

1. INTRODUCTION

Emerging markets have been marked by several articles of volatility spillovers and contagion (Bodart & Candelon, 2009; Beirne et al, 2010; Brana & Lahet, 2010). Follow history timeline to review some events that affect to financial market, especially emerging markets that were noted in many scholar research papers recent years, those events are, namely Mexican Peso crisis during 1994-1995 (Truman, 1996; Whitt, Jr., 1996; Griffith-Jones, 1997; Kanas, 2005; Feridun, 2007; Walid et al, 2011), the Asian currency and financial crisis (Radelet & Sachs, 1998; Corsetti et al, 1999; Wong, 1999; Kim et al, 2000) and the devaluation of Thailand's bath in 1997 (Kaminsky et al, 1998), the Russian financial crisis and the collapse of Long-Term Capital Management (LTCM) in 1998 (Feridun, 2004; Forbes, 2004; Saleem, 2009), the market reaction after the terrorist incident on September 11 in 2001 (Johnston & Nedelescu, 2005; Karolyi & Martell, 2010; Suleman, 2012), the Argentine defaulted debt crisis during 1999–2002 (Schuler, 2005; Kehoe, 2003); the U.S. high-yield market sell-off in 2002 (Altman & Bana, 2003; Reilly et al, 2009); the U.S. 2007 Subprime Crisis (Frank et al, 2008; Dooley & Hutchison, 2009;), and the global financial crisis of 2007–2009 (Bunda et al, 2009; Frank & Hesse, 2009; Guillén & Suárez, 2010; Melvin & Taylor, 2009; Rocha & Moreira, 2010; Nier & Merrouche, 2010; Swedberg, 2010; Atkinson et al, 2013). Kanas (2005) and Walid et al (2011) proved evidence of regime dependence between the Mexican currency market and the volatility of some Asian emerging markets. The ruble's massive devaluation followed by sovereign debt default boosted emerging market risk and suppressed commodity exports from emerging markets to Russia (Saleem, 2009). Following Mexico's December 1994 peso devaluation, capital flows out of emerging markets. Foreign banks and other institutional investors from Europe and later the United States, all flush with funds, soon discovered Asia's emerging markets, where interest rates were high and risk was very low because currencies were pegged to the U.S. dollar (Wong, 1999). Stock returns of the Asian countries then moved again to the high volatility regime in October 1997 corresponding to the Asian currency crisis (Tai, 2007; Walid et al, 2011). The events Russian crisis of 1998, the Brazilian crisis of 1999, and stock market volatility increased in late 2001 as a result of the 9/11 terrorist attack affects all the Asian stock markets and a spell of high volatility (Walid et al, 2011). Besides, the Asian markets switch to a regime of high volatility in mid 2007 may be attributed to the subprime crisis in the U.S. (Walid et al, 2011). Besides, capital flows to emerging markets increased dramatically due mainly to the structural changes and economic liberalization in the 1990s (Bekaert et al, 1997; Bekaert & Harvey, 2000).

Therefore, emerging markets offered high rates of returns, high volatility, high risk in comparison to developed markets as well as low correlation with developed markets during the first half of the 1990s (Harvey, 1995; Bekaert et al, 1997; Bekaert & Harvey, 2000). However, the performance characteristics of emerging markets changed over the last half of the 1990s because of financial crises as well as the financial and economic integration of emerging markets with the developed markets (Bekaert et al, 1997; Bekaert & Harvey, 2000; Bruner et al, 2003; Li et al, 2003; Kortas et al, 2005; Fan et al, 2011). Further, there are many researchers studied about firms in emerging markets (Klapper & Love, 2004; Bleakley & Cowan, 2010; Pinegar & Ravichandran, 2010; Fan et al, 2011; Liu, 2011), the diversification benefits of investing in emerging markets (Kargin, 2002; Bruner et al, 2003; Li et al, 2003; Guest editorial, 2006; Jung et al, 2009; Naranjo & Porter, 2007; Walid et al, 2011), and interest-rate volatility in emerging markets (Hamilton & Susmel, 1994; Edwards & Savastano, 1998) making these topics popular recent years. The previous researchers studied about the emerging markets in specific regions such as Europe, Latin America (Chang et al, 2004), Middle East and North Asia - MENA (Lagoarde-Segot & Lucey, 2008; Jahan-Parvar & Waters, 2009), and Asia (Bekaert & Harvey, 1995; De Santis & Gerard, 1997; Nakagawa, 2007; Tai, 2007) or all emerging market countries in general (Canela & Collazo, 2007; Naranjo & Porter, 2007; Aggarwal & Goodell, 2009; Beirne et al, 2010). The Asian emerging markets have greater predilection towards markets (Nakagawa, 2007; Aggarwal & Goodell, 2009).

The earlier researchers realized that there are not many studies which have specifically investigated the performances of ETFs that purposely dig into global emerging markets equity indexes (Blitz & Huij, 2012). However, there are several papers for emerging equity markets and the impact of foreign exchange (FX) rate changes on stock market volatility of emerging markets (Bekaerta & Harvey, 1997; Kanas, 2005; Kortas et al, 2005; Canela & Collazo, 2007; Aloui & Jammazi, 2009; Wang & Theobald, 2008; Donadelli & Prosper, 2011; Walid et al, 2011). Global emerging markets are countries such as South Korea, China, India, Brazil, South Africa and Russia, which have become increasingly important to investors due to their fast growing economies (Klapper et al, 2004; Blitz & Huij, 2012). Besides, stocks in emerging markets are less liquid and have higher trading costs than stocks in developed markets (Domowitz et al, 2001; Bekaert et al, 2002; Chiyachantana et al, 2004; Blitz & Huij, 2012). The return in emerging markets is structurally higher than in the U.S., Europe and the Japan-Pacific regions (Harvey, 1995; Dey 2005; Phylaktis & Xia, 2006; Blitz & Huij, 2012). The diversification benefits are larger in emerging than developed markets (Li et al, 2003;

Jung et al, 2009; Naranjo & Porter, 2007; Walid et al, 2011). At another side, long memory is more often found in emerging market stock returns than in developed markets (Barkoulas et al, 2000; Wright, 1999; Sourial, 2002; Limam, 2003; Assaf, 2006; Floros et al, 2007; Kang & Yoon, 2007). Since stock markets in emerging countries have become an important source for global portfolio diversification, understanding of the dynamic behavior of stock returns in these countries is crucial for portfolio managers, policy makers, and researchers (Kasman et al, 2009).

The world's emerging markets have become the focus of sustained research in the past two decades. Emerging markets comprise the majority of the world's people and land, and they continue to grow faster than the developed world. They are increasingly recognized as a diverse set of business, cultural, economic, financial, institutional, legal, political and social environments within which to test, reassess and renew received wisdoms about how the business world works, to gain deeper insights into prevailing theories and their supporting evidence, and to make new discoveries that will enhance human welfare in all environments including the world's poorest countries, the developing world, the transition countries and the developed world. The world is dominated by emerging economies in terms of population and geographic size. Emerging countries make up about three quarters of the world's land mass and emerging markets are diverse in culture, language and politics (Kearney, 2012). The emerging markets in Asia include China, India, Indonesia, Israel, Jordan, Malaysia, Pakistan, the Philippines, South Korea, Taiwan, Thailand, Turkey and the UAE (Bleakley & Cowan, 2010; Kearney, 2012). Within those Asia emerging countries, Philippines, Taiwan, Indonesia and South Korea with volatilities higher than 30% (Bekaert & Harvey, 1997). In the past two decades, emerging markets have grown swiftly, with the rise of several largest economies such as Russia, China and India (Kraeussl & Logher, 2010; Rocha & Moreira, 2010; Fan et al, 2011). The two largest Asian emerging countries, China and India, are expected to lead this growth. Thailand is another large emerging market that is well-known to international investors (Bekaert & Harvey, 1997). In addition, emerging market (EM) research is a fascinating multidisciplinary area that incorporates disciplines as disparate as anthropology, genetics, geography, history, philosophy, psychology, physics and sociology in addition to the standard business disciplines of economics, finance, international business and management (Kearney, 2012). Researchers dig in emerging markets more and more. Notable examples include Fifield et al (1999) who examined the criteria defining emerging markets and summarized the previous two decades' work, focusing mostly on equity markets. Bekaert & Harvey (1997, 2003) reviewed research on finance in emerging markets, focusing mainly on

20 countries with the longest available spans of data on the International Finance Corporation's (IFC) emerging market database. Other researchers have provided surveys of topics in EM research. Khilji (2003) reviewed financial crises; Phylaktis (2006) focused on asset management, contagion, corporate finance and market integration; and Lien and Zhang (2008) surveyed derivative markets. More recently, Fan et al (2011) provided an authoritative overview of how key institutional forces in emerging markets such as government quality, the extent of state ownership, and the degree of financial development, impact upon the structures and behaviors of firms including their investments, financing, governance and growth. They suggested areas for new EM research including government incentives, informal enforcement procedures, family firms and network organizations.

Malaysia and Russia are the most power distance emerging countries (Elenkov, 1998; Borker, 2012). Russia is the most uncertainty-avoidance emerging markets (Voros & Choudrie, 2011; Rapp et al, 2010; Filippov, 2012). India and the Philippines are most comfortable with uncertainty and ambiguity emerging markets (Lang & Maffett, 2011; Brandao-Marques et al, 2013). The potential return of emerging markets remains higher in comparison to those of developed market counterparts (Kortas et al, 2005). Bruner et al (2003) noted that at the end of December 2002, emerging markets represent 10.5% of the world market capitalization while they account for 20% of the world GDP. Due to many facts of advantages in Asia emerging markets, more attention has been paid by not only international scholars but also international investors. Therefore, the scholars studied Asian emerging equity or FX markets and Asian emerging stock markets more and more year by year (Brunetti et al, 2008; Flavin et al, 2008; Wang & Theobald, 2008; Bodart & Candelon, 2009; Beirne et al, 2010; Bleakley & Cowan, 2010; Brana & Lahet, 2010; Walid et al, 2011). The sample consists of some Asia countries emerging markets, namely Indonesia, Malaysia, Philippines, South Korea, and Thailand from year 2008 to year 2013. Since emerging markets are less integrated than developed markets, the diversification benefits available from including them in international momentum investing strategies should be large. Naranjo and Porter (2007) examined the diversification benefits from including emerging markets in an international momentum investment strategy.

Section 2 of the paper reviews some literatures of ARCH models and ARFIMA models, namely ARIMA, ARFIMA, EGARCH, FIGARCH, HYGARCH, ARFIMA-FIGARCH, and ARFIMA-HYGARCH. Section 3 discusses about methodology and data analysis. Section 4 reports some applications and empirical results of EGARCH, ARFIMA, ARFIMA-FIGARCH, and ARFIMA-HYGARCH. The four models are applied to seven currency ETFs series in Asian emerging markets covering the 2008-2013 periods. Section 5 concludes the paper.

2. LITERATURE REVIEWS

2.1 ARIMA model

ARMA(p,q) models are discussed as combinations of the AR and MA models. These are called autoregressive moving an average (ARMA) model, which is defined as:

$$\Phi(L)y_t = \theta(L)\varepsilon_t$$

Where ε_t is purely random process with mean zero and variance σ^2. It can be rewritten using the lag operator L as:

$$\Phi(L) = (1 - \alpha_1 L - \alpha_2 L^2 - \ldots - \alpha_p L^p)$$

Where $\Phi(L)$ and $\theta(L)$ are polynomials of orders p and q, respectively, defined as

$$y_t = \alpha_1 y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

For example, the ARMA(1,1) process is:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$$

In terms of the lag operator L this can be written as:

$$(1 - \alpha_1 L)y_t = (1 + \theta_1 L)\varepsilon_t \text{ or } y_t - \alpha_1 y_{t-1} = \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

$$y_t = [(1 + \theta_1 L)/(1 - \alpha_1 L)]\varepsilon_t$$

Since ε_t is a pure random process with variance σ^2 we get

$$\mathrm{Var}(y_t, y_{t-1}) = \{[(\alpha + \theta)(1 + \alpha\theta)]/(1 - \alpha^2)\}\ \sigma^2 \text{ hence}$$

$$\rho(1) = \mathrm{cov}(y_t, y_{t-1})/\mathrm{var}(y_t) = [(\alpha + \theta)(1 + \alpha\theta)]/(1 + \theta^2 + 2\alpha\theta)$$

Successive values of $\rho(k)$ can be obtained from the recurrence relation $\rho(k) = \alpha\rho(i-1)$ for $k \geqq 2$.

Thus, the ACF for an ARMA(1,1) process is such that the magnitude of ρ_1 depends on both *a* and ɵ. In the operator Δ=1-L so that $\Delta y_t = y_t - y_{t-1},\ \Delta^2 y_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})$, and so on, $\Delta^d y_t$ is supposed a stationary series that can be represented by an ARMA(p,q) model. Then, y_t can be represented by an autoregressive integrated moving average model, ARIMA(p,d,q). The model is called an integrated model because the stationary ARMA model that is fitted to the differenced data has to be summed or “integrated” to provide a model for the nonstationary data.

2.2 EGARCH model

EGARCH (Nelson, 1991) and FIGARCH (Baillie et al, 1996, Ding & Granger, 1996) are variants of ARCH model’s conditional volatility which have been proposed by Engle in 1982. All of these models, and many other cases that might be devised, fall into the class in which the conditional variance at time t is an infinite moving average of the squared realizations of the series up to time t − 1. EGARCH is short for Exponential Generalized Auto Regressive Conditional Heteroskedasticity. The GARCH process is a popular stochastic process which has been fairly successful in modeling financial time series (Engle, 2004). The exponential GARCH (EGARCH) model is where the logarithm of the conditional variance is modeled (Nelson, 1991). EGARCH models are which describes the dynamics of log volatility (of which the log range is a linear proxy) (Nelson, 1991, Pagan & Schwert, 1990; Hentschel, 1995). EGARCH models can accommodate asymmetric volatility (often called the "leverage effect"), where increases in volatility are associated more often with large negative returns than with equally large positive returns. EGARCH models provide forecasts of future log volatility (or log variance). Since periods of currency ETFs seem to be clustered in time, an asymmetrical EGARCH model (Nelson, 1991) is therefore estimated to accommodate for volatility clustering and for asymmetry in the volatility process. Noting that, an EGARCH model can be represented as an ARMA process in terms of the logarithm of conditional variance and thus always guarantees that the conditional variance is positive. Nelson (1991) proposed the following exponential GARCH (EGARCH) model to allow for leverage effects:

$$\sum_{i=1}^{p} \alpha_i \frac{|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} \beta_j h_{t-j}$$

2.3 ARFIMA model, ARFIMA-FIGARCH model and ARFIMA-HYGARCH model

2.3.1 ARFIMA model

Granger and Joyeux (1980) and Hosking (1981) proposed an ARFIMA (Autoregressive fractionally integrated moving average) model which is: $\Phi(L)(1-L)^d (X_t - \mu)=\theta(L)\varepsilon_t$ and proposed the method to fit long-memory data. ARFIMA(p,d,q) is written as follow: $\varphi(L)\Delta^d y_t = \delta + \theta(L)u_t$ with $\varphi(L) = (1 - \varphi_1 L - \ldots - L^p)$ and $\theta(L) = (1 - \theta_1 L - \ldots - \theta_q L^q)$ where: δ = a constant term; $\theta(L)$ = the MA operator at order q; u_t = an error term; $\varphi(L)$ = the AR operator at order p; $\Delta^d y_t$ = the differencing operator at order d of time series data y_t. ARFIMA (Autoregressive fractionally integrated moving average) model is time series model that generalized ARIMA (autoregressive integrated moving average) model by allowing non-integer values of the differencing parameter. These models are useful in modeling time series with long memory - that is, in which deviations from the long-run mean decay more slowly than an exponential decay. A general multiplicative seasonal ARIMA model for time series Z_t is as follows:

$$\varphi(L)\Phi(L^s)(1-L)^d(1- L^s)^D Z_t = \theta(L)\rho(L^s)\alpha_t \text{ where:}$$

L = a backshift or lag operator ($B_{zt} - Z_{t-1}$);

S = seasonal period;

$\varphi(L) = (1 - \varphi_1 L - \ldots - L^p)$ is the non-seasonal AR operator;

$\Phi(L^s) = (1 - \Phi_1 L^s - \ldots - \Phi_s L^s)$ is the seasonal AR operator;

$\theta(L) = (1 - \theta_1 L - \ldots - \theta_q L^q)$ is the non-seasonal MA operator;

$\rho(L) = (1 - \rho_1 L^s - \ldots - \theta_0 L^{Qs})$ is the seasonal MA operator;

$(1 - L)^d(1 - L^s)$ = non-seasonal differencing of order d and seasonal differencing of order D.

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 shock 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 anti-persistence when $-0.5<d<0$ (Baillie et al., 1996). The process is non-stationary if $d \geqq 0.5$ (Galbraith & Zinde-Walsh, 2001). While it is stationary but noninvertible process if $d \leqq -0.5$, making the time series impossible to model by any autoregressive process.

2.3.2 FIGARCH model:

The FIGARCH (Fractional integrated general autoregressive conditional heteroskedasticity) model of Baillie et al (1996):

$$\sigma^2_t = \{1-[1 - \beta(L)]^{-1} (1-L)^d \Phi(L)\} \varepsilon^2_t$$

Fractionally Intergrated Garch (FIGARCH) model is proposed to determine long memory in return volatility. Baillie et al (1996) have extended the traditional GARCH model to capture the long memory component in the return's volatility. The FIGARCH(p,d,q) process is as follow:

$$[\Phi(L)(1 - L)^d]\varepsilon^2_t = \omega + [1 - \beta(L)](\varepsilon^2_{t-} \sigma^2_{t})$$

Where $v_t = u^2_t - \sigma^2_{t,t}$ $0<d<1$, $\Phi(L) = \sum_{i=1}^{m-1} \varphi_i L^i$ is of order m-1, and all the roots of $\Phi(L)$ and $[1 - \beta(L)]$ lie outside the unit circle.

The FIGARCH model is derived from standard GARCH model with fractional different operator $(1-L)^d$. The FIGARCH(p,d,q) model is reduced to the standard GARCH when d=0 and becomes IGARCH model when d=1. It is well known that for $0<d\leq 1$ the FIGARCH(p,d,q) process has an undefined unconditional variance. However, the process does possess cumulative impulse response weights with a finite sum. This property makes the

FIGARCH model different from other possible forms of long memory ARCH models. Further, in terms of hyperbolic memory, an alternative definition for the persistence properties of the FIGARCH process makes more precise the distinction of the FIGARCH model from the shorter (geometric) memory cases represented by the GARCH and IGARCH processes (Davidson, 2004).

2.3.3 HYGARCH Model

The HYGARCH model was introduced as a generalization of FIGARCH with hyperbolic convergence rates (Davidson, 2004). These models fall in the class of models where the conditional variance at time t is an infinite moving average of the squared realizations of the series up to time t − 1. The proposed HYGARCH model permits both the existence of second moments and more flexibilities than the IGARCH and FIGARCH models (Kwan et al, 2012). Consider, for comparability with the previous cases, the form:

$$\Theta(L) = 1- \frac{\delta(L)}{\beta(L)} \left(1 + \alpha((1-L)^d - 1)\right) \quad \alpha \geq 0,\ d \geq 0.$$

Note that provided $d > 0$, $S = 1 - \frac{\delta(1)}{\beta(1)} (1 - \alpha)$.

It is known that a GARCH (p,q) model can be rewritten as an ARMA model in squares:

$$\Phi(L)\epsilon_t^2 = \alpha_0 + \beta(L)v_t,$$

Where $v_t = \epsilon_t^2 - h_t$ or the term can be rewritten as:

$$h_t = (\alpha_0 / \beta(1)) + \left(1 - \frac{\varphi(L)}{\beta(L)}\right) \epsilon_t^2 = \alpha_0 + \lambda(L)\epsilon_t^2$$

Davidson (2004) shows that the HYGARCH is capable of modeling the volatility dynamics in three Asian currencies during the crisis period 1997-1998. Niguez and Rubia (2006) apply the HYGARCH model to a portfolio of five exchange rates and report that it clearly outperforms simpler GARCH variants in terms of out-of-sample forecasting. Tang and Shieh (2006) compare the performance of FIGARCH and HYGARCH models in predicting Value-at-Risk for three stock index futures markets.

2.3.4 ARFIMA-FIGARCH model

In several studies discussions, the ARFIMA-FIGARCH model was applied to show significant evidences of long memory model in Japanese equity (Nagayasu, 2003), in financial stock exchange (Cheong, 2007), in Istanbul stock exchange (Korkmaz et al 2009), in Turkish stock market (Kasman & Torun, 2007), and in future markets in Turkey (Yalama et al, 2011). Besides, ARFIMA-FIGARCH model also showed a presence of dual long memory model in Daily Exchange Rates (Beine et al, 2002), in Korean stock market (Kang & Yoon, 2012). In addition, the ARFIMA-FIGARCH model suggested long memory in the conditional mean and variance of financial processes (Conrad & Karanasos, 2005; Fiszeder, 2006). Further, the ARFIMA-FIGARCH model was applied to test the efficiency of Japanese equity market (Nagayasu, 2003), to predict stock returns (Sivakumar & Mohandas, 2009). Moreover, ARFIMA-FIGARCH model was also used for forecasting (Chokethaworn et al, 2010a, 2010b). In short, ARFIMA-FIGARCH model is an association between ARFIMA model and FIGRACH model (Kang & Yoon, 2012). In the other words, the ARFIMA-FIGARCH model is an association of appropriate lags ARFIMA (n,s)-FIGARCH(p,q) (Sandu, 2009).

2.3.5 ARFIMA-HYGARCH model

The ARFIMA-HYGARCH model is a long-memory model for the conditional mean and the conditional variance as well (Kwan et al, 2012). An ARFIMA(1,d,0)-HYGARCH(1,dFG,1) model was applied to ten daily exchange rates series and also to some Asian exchange rates over the 1997 crisis period (Davidson, 2004). Davidson (2004) used the Student's t distribution to fit the GARCH models in order to estimate the ARFIMA–HYGARCH models. The method was proposed by Bollerslev (1987).

Let {yt} be a stationary and ergodic time series generated by the ARFIMA(p,dARF,q) process,

$$(1-L)^{d_{ARF}}\ \varphi(L)y_t = \psi(L)e_t, \quad (1)$$

In which the error sequence {et} follows the HYGARCH(r,dFG,s) model,

$$e_t = \varepsilon_t h_t^{1/2},\ h_t = \gamma + \{1 - [1 - \alpha + \alpha(1-L)^{d_{FG}}]\frac{\varphi(L)}{\beta(L)}\}e_t^2, \quad (2)$$

Where L is the back-shift operator, $\varphi(x) = 1 - \sum_{k=1}^{p} \varphi_k x^k$, $\psi(x) = 1 - \sum_{k=1}^{q} \psi_k x^k$, $\delta(x) = 1 - \sum_{k=1}^{r} \delta_k x^k$, $\beta(x) = 1 - \sum_{k=1}^{s} \beta_k x^k$, and p, q, r and s are known positive integers; also take the innovation sequence {εt} to be identically and independently distributed (i.i.d.) with mean zero and variance one, and

$$(1 - L)^d = 1 - \sum_{j=1}^{\infty} \frac{d\Gamma(j-d)}{\Gamma(1-d)\Gamma(j+1)} L^j \quad \text{as } 0<d<1.$$

Denoting $\theta_V = (\gamma, \beta_1, \ldots, \beta_s, \delta_1, \ldots, \delta_r, d_{FG}, \alpha)'$, model (2) can be rewritten into the following ARCH(∞) form:

$$h_t = \gamma + \pi(L)e_t^2 = \gamma + \sum_{j=1}^{\infty} \pi_j e_{t-j}^2 \quad (3)$$

Where the π_j's are functions of θ_V. Let $\theta_M = (\varphi_1, \ldots, \varphi_p, \psi_1, \ldots, \psi_q, d_{ARF})'$. Then $\theta = (\theta'_M, \theta'_V)'$ is the parameter vector of models (1) and (2), called the ARFIMA(p,d_{ARF},q)–HYGARCH(r,d_{FG},s).

The parameters $\alpha \geq 0$, $0 < d_{FG} \leq 1$ and $\sum_{j=1}^{\infty} \pi_j < 1$; the polynomials δ(x) and β(x) have no common root and all the roots of these two polynomials are outside the unit circle. When $d_{FG} = 0$, the conditional variance model becomes an ordinary GARCH model. Thus, the focus of this article will be on the range $0 < d_{FG} \leq 1$. There are two kinds of memory to be recognized: hyperbolic decaying memory and geometric decaying memory, with the former being defined as long memory (Davidson, 2004). For model (2), when $0 < d_{FG} < 1$, $\pi_j = O(j-1-d)$, i.e. the coefficients decay hyperbolically, and the conditional variance h_t in (3) or (2) will exhibit the long-memory effect. The condition $\sum_{j=1}^{\infty} \pi_j < 1$ is necessary and sufficient for the ARCH(∞) process (3) to be strictly stationary with finite second moment (Giraitis et al., 2000; Kokoszka & Leipus, 2000l; Zaffaroni, 2004).

3. METHODOLOGY AND DATA ANALYSIS

The data are Emerging Markets Equities ETFs that are obtained from yahoo finance and ETF database website at http://etfdb.com/etfdb-category/emerging-markets-equities/. The collected data of seven ETFs are from seven Asian emerging countries, those are Wisdom Tree Indian Rupee Fund (ICN), Market Vectors Indonesia Index (IDX), iShares MSCI Malaysia Index Fund (EWM), Market Vectors Russia ETF (RSX), and iShares MSCI Thailand Investable Market Index Fund (THD), SPDR S&P China ETF (GXC), and Market Vectors Vietnam ETF (VNM) starting from the date April 02, 2008 up to December 31, 2013. That means about 5 years data was used for the further computation. The database information is shown in table 1.

Table 1: The Sample Size and Period of 7 ETFs

List of Asian emerging markets ETFs	Start of Data	Obs	Mean	Std. Dev.	Skew.	Kurt.	J-Bera
iShares MSCI Malaysia Index Fund (EWM)	2008-4-02	1258	0.007321	0.6286	0.0509	3.4851	637.20***
SPDR S&P China ETF (GXC)	2008-4-02	1449	0.001823	1.0660	0.3087	8.9619	4872.1***
Wisdom Tree	2008-5-23	1220	0.000469	0.4148	0.5899	22.853	26620***

Indian Rupee Fund (ICN)							
Market Vectors Indonesia Index (IDX)	2009-1-21	1054	0.056281	0.9049	0.1139	2.8006	346.74***
Market Vectors Russia ETF (RSX)	2008-4-02	1258	-0.019551	1.5115	-0.4489	9.0375	4323.5***
iShares MSCI Thailand Investable Market Index Fund (THD)	2008-4-02	1243	0.019924	0.9603	-0.2868	5.1295	1379.7***
Market Vectors Vietnam ETF (VNM)	2009-8-17	1102	-0.012829	0.8161	-0.1390	1.0199	51.308***
Source: Yahoo Finance; http://etfdb.com/etfdb-category/emerging-markets-equities/ Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.							

The time series of EWM has sample size 1258 observations during (April 2, 2008 – April 1, 2013). The time series of GXC has sample size 1449 observations during (April 02, 2008 – December 31, 2013). The time series of ICN has sample size 1220 observations during (May 23, 2008 – April 01, 2013). The time series of IDX has sample size 1054 observations during (January 21, 2009 – April 01, 2013). The time series of RSX has sample size 1258 observations during (April 02, 2008 – April 01, 2013). The time series of THD has sample size 1243 observations during (April 02, 2008 – March 8, 2013). The time series of VNM has sample size 1102 observations during (August 17, 2009 – December 31, 2013). The average return form of seven ETFs and the standard deviation of these ETFs average returns are showed in table 1. In table 1, the values of Skewness, Excess Kurtosis, and Jarque-Bera probability will be showed.

Skewness value of EWM is 0.050945; comes in the form of “positive Skewness”. Data points are skewed to the right (positive skew) of the data average. With a skewness of 0.050945 – between +0.5 and +1, the distribution is moderately skewed, the sample data for Malaysian ETF (April 02, 2008 – April 01, 2013) is moderately skewed. Positive excess kurtosis (leptokurtic) = 3.4851 (>0). Compared to a normal distribution, its central peak is higher and sharper, and its tails are longer and fatter. Jarque-Bera's p-value is 4.3065e-139; the series is not normally distributed. Skewness value of GXC is 0.30874; comes in the form of "positive Skewness". Data points are skewed to the left (positive skew) of the data average. With a skewness of 0.30874 – between +0.5 and +1, the distribution is moderately skewed, the sample data for Chinese ETF (April 02, 2008 – December 31, 2013) is moderately skewed. Positive excess kurtosis (leptokurtic) is 8.9619 (>0). Compared to a normal distribution, its central peak is higher and sharper, and its tails are longer and fatter. Jarque-Bera's p-value is 8.6328e-163; the series is not normally distributed. Skewness value of ICN is 0.58990; comes in the form of "positive Skewness". Data points are skewed to the right (positive skew) of the data average. With a skewness of 0.58990 – between +0.5 and +1, the distribution is moderately skewed, the distribution is moderately skewed, the sample data for Indian ETF (May 23, 2008 – April 01, 2013) is moderately skewed. Positive excess kurtosis (leptokurtic) is 22.853 (>0). Compared to a normal distribution, its central peak is higher and sharper, and its tails are longer and fatter. Jarque-Bera's p-value is 0.00000; the series is normally distributed. Skewness value of IDX is 0.11394; comes in the form of "positive Skewness". Data points are skewed to the right (positive skew) of the data average. With a skewness of 0.11394 – between −0.5 and +0.5, the distribution is approximately symmetric, the distribution is moderately skewed, the distribution is moderately skewed, the sample data for Indonesian ETF (January 21, 2009 – April 01, 2013) is moderately skewed. Positive excess kurtosis (leptokurtic) is 2.8006 (>0). Compared to a normal distribution, its central peak is higher and sharper, and its tails are longer and fatter. Jarque-Bera's p-value is 5.0958e-076; the series is not normally distributed. Skewness value of RSX is -0.44896; comes in the form of "negative Skewness". Data points are skewed to the right (negative skew) of the data average. With a skewness of -0.44896 – between −0.5 and +0.5, the distribution is approximately symmetric, the distribution is moderately skewed, the distribution is moderately skewed, the sample data for Russian ETF (April 02, 2008 – April 01, 2013) is moderately skewed. Positive excess kurtosis (leptokurtic) is 9.0375 (>0). Compared to a normal distribution, its central peak is higher and sharper, and its tails are longer and fatter. Jarque-Bera's p-value is 0.00000; the series is normally distributed. Skewness value of THD is -0.28681; comes in the form of "negative skewness". Data points are skewed to the left (negative skew) of the data average. With a skewness of -0.28681 – between -0.5 and 0.5, the sample data for Thailand ETF (April 02, 2008 – March 8, 2013) are approximately symmetric. Positive excess kurtosis (leptokurtic) = 5.1295 (>0). Compared to a normal distribution, its central peak is higher and sharper, and its tails are longer and fatter. Jarque-Bera's p-value = 2.4643e-300, the series is not normally distributed. Skewness value of VNM is -0.13902; comes in the form of "negative skewness". Data points are skewed to the left (negative skew) of the data average. With a skewness of -0.13902 – between -0.5 and 0.5, the sample data for Vietnamese ETF (August 17, 2009 – December 31, 2013) are approximately symmetric. Positive excess kurtosis (leptokurtic) = 1.0199 (>0). Compared to a normal distribution, its central peak is higher and sharper, and its tails are longer and fatter. Jarque-Bera's p-value = 7.2215e-012, the series is not normally distributed.

The result of ARCH (1-5) test (see table 1) shows that all the probability values of the six ETFs are significant. The null hypothesis is significantly rejected of No ARCH Effects. Then, another test is needed to see if these ETFs data have serial correlation. Besides, the Q-statistics tells whether the series has serial correlation. This study selected 10 lags. The number should not be significant and must accept the null hypothesis of No serial correlation. As the results, probability values of VNM and RSX are not significant so the null hypothesis of no serial correlation is accepted for these two ETFs. In addition, normality test for this data obviously shows that skewness results of RSX, THD, and VNM are negative, it means the skewness slopes of the ETFs move to the left because the values smaller than 0. In the other words, they are not normal curves. in the opposite, skewness results of EWM, GXC, ICN and IDX are positive, it means the skewness slopes of the ETFs move to the right because the values bigger than 0. So they are not normal curves. Kurtosis values of all seven ETFs are positive and they tend to pointed curve because the values are bigger than 0. The results of J.Bera probability values test are all significant. In fact, the data are accepted or the error terms are distributed normally. Q-statistic results of this test are all higher than chi square lag {Q < Chisq(lag)} so the values should not be significant and must accept the null hypothesis of No serial correlation. However, there are only two ETFs RSX and VNM are not significant so the null hypothesis of no serial correlation is accepted for these two ETFs.

Next, ARFIMA, ARFIMA-FIGARCH and ARFIMA-HYGARCH models are used for the analyses and final results.

4. APPLICATIONS AND EMPIRICAL RESULTS

First of all, seven ETFs index data were all tested unit root. Then, ARMA model and EGARCH model were applied as filters. In ADF test, the null hypothesis is "there is a unit root". The null hypothesis is tested and the results are given in the below table for the selected series. ADF statistics of seven ETFs are all negative or smaller than 0. It means the probability of the ETFs during the periods having unit root. The results are showed in table 2.

Table 2: Summary Statistics of ARMA and EGARCH filtering

List of Asian emerging markets ETFs	ADF	ARMA	AIC	LM test	ARCH-LM	EGARCH	AIC	ARCH-LM
EWM	-42.3994***	(1,2)	1.8798	0.236475	121.2391 (0.00)***	(3,2)	1.5345	2.5975 (0.2729)
GXC	-19.3414***	(3,3)	2.9231	1.615338	294.2034 (0.00)***	(3,2)	2.3380	4.2917 (0.1170)
ICN	-23.0981***	(2,3)	1.0459	3.710136	171.6569 (0.00) ***	(3,3)	0.5886	8.9307 (0.0115)
IDX	-17.4146***	(3,3)	2.6304	2.877948	66.6525 (0.00) ***	(3,1)	2.3389	2.9712 (0.2264)
RSX	-27.3490***	(2,2)	3.6525	7.013959	218.4240 (0.00) ***	(3,2)	2.9447	3.2055 (0.2013)
THD	-40.8345***	(2,3)	2.7385	0.081348	139.1052 (0.00) ***	(3,3)	2.3331	0.1976 (0.9059)
VNM	-14.3941***	(2,3)	2.4217	0.338294	18.9644 (0.00) ***	(2,3)	2.3633	1.0013 (0.6061)

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

The augmented Dickey-Fuller (ADF) statistics used in the test are negative numbers. The more negative it is, the stronger the rejection of the hypothesis that there is a unit roots at some level of confidence. In this case, with four lags, the models that include constants and time trends are estimated using sample of 1258 (EWM), 1449 (GXC), 1220 (ICN), 1054 (IDX), 1258 (RSX), 1243 (THD), and 1102 (VNM) observations and yields the DF statistic of -42.39947, -19.34147, -23.09818, -17.41467, -27.34902, -40.83453, and -14.39410 constituted rejections at the p-value of 0.01, 0.05 and 0.1 (or at the 1% level, 5% level and 10% level) the null hypothesis of a unit root will be rejected in a given time series. Moreover, the data is already stationary using no difference parameters and 4 lags, so ARMA can be used. Significant value for the ADF is required. This means that the null hypothesis of the variable having a unit root/non-stationary is rejected. The significant result in ADF test shows that ARMA should be employed in modeling the data because neither an integrating nor differencing parameter is necessary. Further, to model these time series observations dependence, ARMA (1,2) with the smallest AIC equal to 1.879896 is the best model for Malaysian ETF during the periods. ARMA (3,3) with the smallest AIC equal to 2.92314 is the best model for Chinese ETF during the periods. ARMA (2,3) with the smallest AIC equal to 1.045957 is the best model for Indian ETF during the periods. ARMA (3,3) with the smallest AIC equal to 2.630493 is the best model for Indonesian ETF during the periods. ARMA (2,2) with the smallest AIC equal to 3.652500 is the best model for Russian ETF during the periods. ARMA (2,3) with the smallest AIC equal to 2.738533 is the best model for Thailand ETF during the periods. ARMA (2,3) with the smallest AIC equal to 2.421753 is the best model for Vietnamese ETF during the periods. Indian ETF has the smallest AIC compare to the AIC values of the other six ETFs. Besides, LM test probability values of Malaysian, Chinese, Thailand, Vietnamese ETFs are 0.236475, 1.615338, 0.081348, and 0.338294 all smaller than 1.96, accept the null hypothesis of no first order serial correlation up to lag order 2. The Serial correlation LM test result showed that there is serial correlation in all significance levels. Furthermore, ARCH tests are applied to the residual series, to ensure that the null hypothesis of no ARCH effect is not rejected due to the failure of the pre-whitening linear models. The ARCH-LM tests up to lag order 2 are significant for all ETFs. The p-values exceed zero so it indicates the acceptance of the null hypothesis of model adequacy at significance level 0.01. Thus, ARCH LM-tests indicate that volatility is serially correlated over time.

Other ARCH models have also been estimated i.e. EGARCH model for the given time series (see table 9). The estimation results are also given in the above table. EGARCH (3,2) is the variance equation in the estimated ARCH model for Malaysian ETF. EGARCH (3,2) is the variance equation in the estimated ARCH model for Chinese ETF. EGARCH (3,3) is the variance equation in the estimated ARCH model for Indian ETF. EGARCH (3,1) is the variance equation in the estimated ARCH model for Indonesian ETF. EGARCH (3,2) is the variance equation in the estimated ARCH model for Russian ETF. EGARCH (3,3) is the variance equation in the estimated ARCH model for Thailand ETF. EGARCH (2,3) is the variance equation in the estimated ARCH model for Vietnamese ETF. Indian ETF repeatedly has the smallest AIC which equals to 0.588696 compare to the AIC values of the other six

ETFs. After estimating ARCH models, ARCH-LM test has been used to see whether there is any further ARCH error in the series? The results were found that there was no evidence of any further ARCH in the given time series. The ARCH-LM values of seven ETFs are 2.597507 (EWM), 4.291723 (GXC), 8.930756 (ICN), 2.971245 (IDX), 3.205501 (RSX), 0.197600 (THD), and 1.001381 (VNM) (see table 9) for EGARCH model respectively and P-values of seven ETFs are smaller than 0.85, only Thailand ETF has the p-value of EGARCH model equal 0.9059 greater than 0.85 in this case for the given time series. This proves that there is no ARCH error remains in the given time series of Thailand ETF. The smallest value of AIC indicates best model. These statistics choose EGARCH model for the given time series. Log likelihood is maximizing for EGARCH model and show that it is the best model.

The most popular long memory model for levels $\{x_t\}$ is the ARFIMA (p,d,q), due to Hosking (1981) and Granger and Joyeux (1980). The FI in ARFIMA stands for "Fractionally Integrated". In other words, ARFIMA models are simply ARIMA models in which the d (the degree of integration) is allowed to be a fraction of a whole number, such as 0.4, instead of an integer, such as 0 or 1. To identify the order of the ARFIMA model, OxMetrics software (Oxmetrics 6.2) was used. ARFIMA (3,d,2) model for Malaysian and Indian ETFs, ARFIMA (2,d,3) for Chinese ETF, ARFIMA (3,d,1) for Indonesian ETF, ARFIMA (3,d,3) for Russian and Thailand ETFs, and ARFIMA (1,d,0) for Vietnamese ETFs. The order of d-parameter is already determined in ARIMA model, which are equal to 0.0215721 (EWM), -0.0599322 (GXC), -0.0850279 (ICN), 0.133201 (IDX), -0.0348419 (RSX), 0.0165658 (THD), and -0.0104116 (VNM).

According to the results in table 3, d-coefficient values of Malaysian ETF, Indonesian ETF, and Thailand ETF are greater than 0 and smaller than 0.5 so the long memory processes or the so-called positive dependence among remote observations exists. Besides, d-coefficient values of Chinese ETF, Indian ETF, Russian ETF, and Vietnamese ETF are greater than -0.5 but smaller than 0. So there is presence of intermediately memory or anti-persistence. From the correlogram, it is observed that the best ARIMA model will be Maximum likelihood estimation of ARFIMA (3,d,2) model for Indian ETF (-634.406951) with the smallest AIC equal to 1.05312615, this AIC value is also the smallest value compare to the AIC values of the other five ETFs. The final estimation results for competing model for the given time series are given in the following table 3.

Table 3: Summary Statistics of ARFIMA, ARFIMA-FIGARCH and ARFIMA-HYGARCH models								
		EWM	**GXC**	**ICN**	**IDX**	**RSX**	**THD**	**VNM**
ARFIMA	**d-coef f.**	0.0215 (0.47)	-0.0599 (0.08)	-0.0850 (0.01)**	0.1332 (0.14)	-0.0348 (0.18)	0.0165 (0.64)	-0.0104 (0.79)
	ARMA	(3,2)	(2,3)	(3,2)	(3,1)	(3,3)	(3,3)	(1,0)
	AIC	1.8779	2.9289	1.0531	2.6400	3.6613	2.7388	2.4381
ARFIMA-FIGARCH	**d-coef f.**	-0.0237 (0.55)	-0.0623 (0.15)	-0.0487 (0.44)	0.0777 (0.28)	0.1399 (0.22)	0.0198 (0.68)	-0.0391 (0.48)
	ARCH	(3,0)	(3,3)	(3,2)	(2,3)	(1,2)	(1,2)	(1,1)
	d-coef f.	0.9943*** (0.00)	1.0161*** (0.00)	0.6550*** (0.00)	0.5995 (0.13)	0.7881*** (0.00)	0.6110*** (0.00)	0.3404*** (0.00)
	AIC	1.5614	2.3513	0.5875	2.3536	2.9552	2.3445	2.3745
ARFIMA-HYGARCH	**d-coef f.**	-0.0243 (0.57)	-0.0974 (0.01)	-0.0381 (0.58)	0.0909 (0.23)	0.1380 (0.24)	0.0191 (0.69)	-0.0550 (0.30)
	ARCH	(1,2)	(3,3)	(3,3)	(3,3)	(1,3)	(2,2)	(0,1)
	d-coef f.	1.0345*** (0.00)	1.1122*** (0.00)	0.6186*** (0.00)	0.8059*** (0.00)	0.7020*** (0.00)	0.5935*** (0.00)	0.0924 (0.51)
	Alpha	-0.0080 (0.33)	-0.0073 (0.45)	0.0125 (0.79)	-0.0374 (0.10)	-0.0187 (0.43)	0.0003 (0.99)	0.7777 (0.54)
	AIC	1.5601	2.3466	0.5894	2.3551	2.9575	2.3472	2.3749
Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.								

The t-probability values are insignificant for all ETFs except Indian ETF (ICN). In short, from the above table 3, AIC value of Indian ETF is the smallest that chooses ARFIMA (3,d,2) as the best model for the given time series. Log likelihood is also going in favor of ARFIMA (3,d,2) model. The estimated ARCH models were also compared for the series to check which model is the best model among the competing models. After comparison, the results showed that EGARCH model is the best model for the series. It is also important to note that ARCH models performed better than ARFIMA model in this case. For ARFIMA model, minimum value of AIC is 1.05312615 (ICN), while for EGARCH model, minimum value of AIC is 0.588696 (ICN) and for ARMA model, minimum value of AIC is 1.045957 (ICN).

Next, a simulation study was considered to evaluate the procedures for estimating the parameters of an ARFIMA-FIGARCH process. In this step, ARFIMA (m,d,l) model was applied in combination with GARCH (p,q) orders to generalize ARFIMA-FIGARCH. As the results, Indian ETF has the smallest AIC which equals to 0.587584. The best model is ARFIMA (3,d,2). Estimation for d-Figarch is 0.6550. So ARFIMA-FIGARCH (3,d,2) model of Indian ETF is the best model. Log-likelihood is also going in favor of the model. After all, ARFIMA-HYGARCH model was generalized. According to the results in table 12, d-coefficient value of Indian ETF, Indonesian ETF, Russian ETF, Thailand ETF, and Vietnamese are equal to 0.618626 (ICN), 0.805914 (IDX), 0.702060 (RSX), 0.593500 (THD), and 0.092488 (VNM) which mean the differencing parameters d-Figarch dictate the long memory property of the volatility with a range of $0<d<1$ that allows for stronger volatility persistence. (See Table 3).

Which model performs better within three models that were estimated? To judge the performance of these models, these models were compared with each other and their forecast performances were also evaluated by using two statistics Akaike info criterion (AIC) and Log likelihood. The comparison and forecast evaluation results are given in the following table for the estimated models (see Table 3). Table 3 shows the comparison and forecast evaluation results of four estimated models for ETFs return of seven emerging markets series. From the statistics, EGARCH model performed better than other three models for Malaysian ETF (EWM), Chinese ETF (GXC), Indonesian ETF (IDX), Russian ETF (RSX), Thailand ETF (THD), and Vietnamese ETF (VNM). While ARFIMA-FIGARCH model performed better for only Indian ETF (ICN). AIC statistics choose EGARCH model among four estimated models as the best model for six out of seven variables. The smaller values of AIC indicate best model among the competing models. Besides, maximum Log likelihood statistics showed that ARFIMA-HYGARCH model is the best model for six variables Malaysian ETF (EWM), Chinese ETF (GXC), Indian ETF (ICN), Indonesian ETF (IDX), Russian ETF (RSX), and Thailand ETF (THD). Only ARFIMA-FIGARCH model performed better for Vietnamese ETF (VNM) in this case.

5. CONCLUSION

After achieving stationary by using unit root testing, ARMA model and ARCH-LM test were applied to test seven ETFs series. Then, various models have been used for seven series to choose the best model. ARMA (1,2), ARMA (3,3), ARMA (2,3), ARMA (3,3), ARMA (2,2), ARMA (2,3), and ARMA (2,3) are the final models for Malaysian ETF (EWM), Chinese ETF (GXC), Indian ETF (ICN), Indonesian ETF (IDX), Russian ETF (RSX), Thailand ETF (THD), and Vietnamese ETF (VNM). After ARMA modeling, ARFIMA model and ARCH models were used to form the AIC as well as the log-likelihood. For this purpose, ARCH-LM test was applied firstly to test whether there is any ARCH error. The test results showed that there were ARCH errors in all series for ARMA model. Later, three different ARCH models, namely EGARCH, ARFIMA-FIGARCH and ARFIMA-HYGARCH models were used for seven series. After estimation of ARCH models ARCH-LM test was repeatedly used to test whether there was any further ARCH error in seven series. The test results showed that there was further ARCH error in Thailand ETF series after estimation of EGARCH models. The best model among the competing models was chosen within the estimated ARCH models for six series. The comparison results concluded that EGARCH model is the final competing model for six series, except Indian ETF (ICN) and ARFIMA-HYGARCH model is the competing models for six series, except Vietnamese ETF (VNM). These all models are good and can be used for forecasting, however, a comparison was made in order to evaluate the forecast performance of these models to choose a single model among the competing models. The performances of asymmetric parameter were insignificant in all series except Indian ETF series in estimation of ARFIMA. The performances of asymmetric parameter are significant in all series, except Indonesian ETF (IDx), in estimations of ARFIMA-FIGARCH model and except Vietnamese ETF (VNM) in estimations of ARFIMA-HYGARCH model. It is important to note that the maximum values of log-likelihood of six series felt in estimations of ARFIMA-HYGARCH model. This empirical evidence proves that ARFIMA-HYGARCH model performs better than ARFIMA-FIGARCH and AFIMA models.

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