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NONLINEARITY AND OR LONG MEMORY IN CONDITIONAL VOLATILITY OF FINANCIAL TIMES SERIES

Yosra Koubaa (corresponding author)
Author Affiliation: LaREMFiQ - IHEC, Sousse University, TUNISIA
Address: B.P. 40 Route de la ceinture, Sahloul III, Sousse 4054, TUNISIA.
yosra.koubaa@yahoo.fr

ABSTRACT: *The most relevant stylized facts of time-varying financial volatility are the asymmetric response to return shocks and the long memory property. These have largely been modeled in isolation. To capture the asymmetry or/and the long memory in conditional variance, three models are employed FIGARCH, LSTGARCH and LSTFIGARCH. The estimation results on daily returns of five major stock indices of the G7 countries and 6 selected emerging markets reveal that for most series there is strong evidence of long memory and asymmetry in their conditional variance. Both emerging and developed markets can be reasonably well modeled using STFIGARCH model except CAC and FTSII which can be much better characterized by FIGARCH. Our findings show that STFIGARCH is the best model and it provides more accurate out of sample forecasts than the LSTGARCH model but the FIGARCH stays as a competing model. We note in particular that the transition between two outer regimes is faster for stock markets of emerging economies than for developed economics where in these markets the changes occur in a smooth manner. This corroborates the usual observation that emerging stock markets may collapse much more suddenly and recover more slowly than the developed stock markets.*

KEYWORDS: Long memory; Asymmetry; nonlinear model; Conditional Volatility; GARCH model

INTRODUCTION

In efficient markets stock prices fully reflects all available information (Fama, 1970). The prices respond quickly and accurately to relevant information. Therefore, the dynamic of efficient stock exchange is characterized by a random walk process, which implies that any shock to stock price is permanent and there is no tendency of mean reversion. However, it is well known that financial returns and squared returns series exhibit highly persistent autocorrelations with a slow or fast mean-reverting phenomenon. To past shocks, the volatility reaction could be transitory or permanent, symmetric or asymmetric depending on the nature of news which induces shifts in the volatility dynamics. For checking if the efficiency hypothesis is true, several

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papers are focused to study the stochastic inherent process of financial times series in short and long run. The empirical evidence shows that the data usually exhibits a set of particular features i.e., mean reversion, volatility clustering, fat tails and long memory. These stylized facts have been long attracting both market professionals and financial academic research which has given a huge impetus to both econometric model building and applied research. The long range dependence is well documented as an intrinsic stylized fact of volatility. This effect was first analyzed by Taylor (1986) for absolute values of stock returns. Engle and Bollerslev (1986) developed the IGARCH process which takes into account the presence of an approximate unit root in the conditional variance but the properties of this model are not attractive from an empirical view. Ding and Granger (1996) argue that the sample autocorrelation function of squared returns initially decreases faster than exponentially, and that only at higher lags does the decrease becomes slower. This pattern suggests that volatility may consist of several components, some of which have a strong effect in the short run but die out quite rapidly.

Several empirical research as Baillie et al.(1996), Dacorogan et al. (1993), Granger and Ding (1996,1997), Heavy (1994), Breidt et al. (1997), Lardic and Mignon (1999) suggest that the long run dependence in the volatility of intraday returns is better characterized by a slowly mean-reverting fractionnary integrated process. Anderson and Bollerslev (1999) show that the volatility fluctuates as a mixture of numerous heterogeneous short-run information arrivals, the observed volatility may exhibit long-run dependencies. As such, the long memory characteristics are an intrinsic feature of the return generating process. Motivated by these observations, Baillie et al. (1996) argue that the FIGARCH process is able to explain the temporal dependency with a slow hyperbolic rate of decay and persistent impulse response weights. However, it is well known that fractional integration is not the only way to originate long memory property. For that, second strands of research have extended the GARCH to accommodating the asymmetry in the volatility clustering. Franses et al. (1998) show that non-linear GARCH models characterize the volatility of different stock returns better than traditional GARCH model. Also, Koutmos (1998) presents results according to which asymmetric models perform better for stock market indices in industrialized countries. Fornari and Mele (1997) employ, for instance, the asymmetric GARCH model, named GJR, proposed by Glosten, Jagannathan and Runkle (1993) (GJR) and volatility switching GARCH (VS-GARCH) for stock returns of selected developed market. Using daily series, the Volatility Switching GARCH process is found to capture asymmetries better than the GJR model. Omran and Avram (2002) also consider these two models and argue that the GJR model outperforms VSGARCH for all stock returns. Similarly, other models are able to capture the sign and size effect of shock on volatility are proposed (see for example

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EGARCH Nelson (1991), TGARCH of Zakoian (1994), QGARCH of Sentana (1995) and LSTGARCH model (Logistic Smooth Transition GARCH) that originally proposed by Hagerud (1997a) and Gonzàlez-Rivera (1998). However, several empirical studies show that asymmetric models cannot fully account for the degree of persistence in the data, suggesting that both long memory and switching regimes can describe volatility of asset return (Kang and Yoon, 2006). To join two strands of literature that had been largely separated long memory and asymmetry, recent econometric studies have defined new approaches that allow for both long memory and asymmetry in volatility (for example, Tse, 1998; Hwang, 2001; Baillie et al., 2009; Asai et al, 2010; Kilic, 2011; Ckili, 2012).

For extending the FIGARCH model to account for different asymmetric dynamics, Tse (1998) have introduced the FIAPARCH, which combines long memory of FIGARCH with Asymmetric Power ARCH model of Ding, Engle and Granger (1993). Diebold and Inoue (2001) show analytically that stochastic regime switching can be easily confused with long memory. The results of Ckilli et al. (2012)show strong evidence of asymmetry and long memory in the conditional variances of three European stock markets and two exchange rate. They found that the FIAPARCH provides more accurate in-sample estimates of long memory and asymmetry in commodity price volatilities and out-of-sample forecasts than other competing GARCH-based specifications. We apply some recent developments in volatility modeling, the FIGARCH long memory volatility model, LSTGARCH asymmetric model and STFIGARCH asymmetric long memory model in stock index returns and we compare the estimation performance of these three models. We use in particular, an new model introduced by Kilic (2011) which can capture both asymmetry and long run dependence simultaneously in volatility process. This model seems very interesting for several reasons presented previously by Kilic (2011). It allows us to explore the asymmetry of smooth transition type within long memory framework without using additional parameters. Furthermore, with the exception of the model of Lee and Degennaro (2000), STGARCH models restrict the threshold parameter to zero. In the STFIGARCH model the threshold parameter could be different from zero which might be important in characterizing the smooth transition volatility dynamics. However, as shown by Fornari and Mele (1997) and Anderson et al. (1999) volatility dynamics may itself depend on the volatility state. In other words, the response of conditional volatility to shocks depends on how turbulent and calm the markets are. For example, during a high-volatility regime, reaction of volatility to news may be more intensive than when such shock takes place during a low-volatility regime. In the STFIGARCH model, the coefficients of the FIGARCH model follow a smooth transition according to logistic transition function. This nonlinear function depends on the choice of transition variable and can generate leverage effects as well as regime-dependent volatility dynamics in long memory volatility. The remainder of this article is organized as follows.

The first section is dedicated to present econometric models. In the second section, we present the methodology and specification tests. Third section discusses the empirical investigation. Section 4 summarizes the main findings of the paper.

Econometric models

FIGARCH model

FIGARCH (p,d,q) model is developed by Bollerslev and Mikkelson (1996) and Baillie et al (1996) as an extension of GARCH model. The FIGARCH (p,d,q) can to take account long memory process with hyperbolic decay, as well as to distinguish between the long memory and short memoryin the conditional variance. The infinite representation of the FIGARCH(p,d,q) can be written as:

$$\sigma_t^2 = \frac{\omega}{\beta(1)} + \left(1 - \frac{\varphi(L)}{\beta(L)}(1-L)^d\right)\varepsilon_t^2 = \frac{\omega}{\beta(1)} + \lambda(L)\,\varepsilon_t^2 \quad (1)$$

Where $\varphi(L) = 1 - \sum_{i=1}^{q} \varphi_i L^i$ and $\beta(L) = 1 - \sum_{i=1}^{q} \beta_i L^i$ are polynomials in the lag operator L with all their roots lying outside the unit circle and $\lambda(L) = \lambda_1 L + \lambda_2 L + \cdots$. Note that in practice, the infinite numbers of lags are truncated at 1000, which is large enough to examine the long memory process. The infinite ARCH terms are given by $\lambda_1 = d + \phi - \beta$, $\lambda_j = \beta\lambda_{j-1} + (f_j - \phi)(-g_{j-1})$ and for all $j \geq 2$ with $f_j = (j-1-d)/j$ and for $j = 1;2;$ .... $g_j = f_j\, g_{j-1} = \prod_{i=1}^{j} f_j$ (Baillie et al., 1996 and Conrad and Haag, 2006). To guarantee the non-negativity of the conditional variance as surely for all t, all the coefficients in the infinite ARCH representation need to be non-negative (See, Baillie et al., 1996, Bollerslev and Mikkelsen, 1996 and Conrad and Haag, 2006, for details).

For the FIGARCH(1,d,1) model conditional volatility is non-negative provided that $\omega > 0; \lambda 1 = d + \phi - \beta \geq 0$, and $\phi \leq (1-d)/2$ for some $0 < \beta < 1$. The parameter d characterizes the long-memory property of hyperbolic decay in volatility because it allows for auto-correlations to die out very slowly at an hyperbolic rate when k increases. The FIGARCH process is that for $0 < d < 1$, it is sufficiently flexible to allow for intermediate ranges of persistence, between complete integrated persistence of volatility shocks associated with $d =$

1, the FIGARCH reduces in this case to IGARCH (1,1) and, as well as to GARCH(1,1) where $d = 0$ with a geometric decay.

LSTGARCH model

The GARCH model fails to account for asymmetry and non linearity in the conditional variance. For this purpose, it has given rise to an array of asymmetric model. We note in particular the Logistic Smooth Transition GARCH (LSTGARCH) developed by Hagerud (1997) and Gonzales-Rivera (1998) which considers two regimes in the conditional variance can be described by a different GARCH(1,1) process:

$$\sigma_t^2 = w + \alpha_1 \varepsilon_{t-1}^2 (1 - F(\varepsilon_{t-1})) + \alpha_1^* \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (2)$$

Where the function $F(\varepsilon_{t-1})$ is the logistic function:

$$F(\varepsilon_{t-1}) = \frac{1}{1 + \exp(-\gamma \varepsilon_{t-1})} \quad (3)$$

with $\gamma > 0$. As the function $F(\varepsilon_{t-1})$ changes monotonically from 0 to 1 as ε_{t-1} increases, the impact of ε_{t-1}^2 on σ_t^2 changes smoothly from α_1 to α_1^*. When the parameter γ is becomes large, the logistic function approaches a step function equals 0 for negative ε_{t-1} and 1 for positive ε_{t-1}. Parameter restrictions for σ_t^2 to be positive are if $w > 0$, $(\alpha_1 + \alpha_1^*)/2 \geq 0$ and $\beta1 > 0$ and to be covariance-stationary if $(\alpha_1 + \alpha_1^*)/2+ < 1+ \beta_1$ the same for the GJR.

SIFIGARCH model

We suppose that a discretely sampled time series process can written as:

$$y_t = \mu + u_t \quad (4)$$

$u_t = \zeta_t \sigma_t$ for $t = 1,\ldots..,T$,

According to Kilic (2011), the STFIGARCH (1,d,1) model is :

$$(1 - \varphi L)^d (1 - L) u_t^2 = \omega + \beta(L) v_t$$

$$(1 - \varphi L) \; (1 - L)^d u_t^2 = \omega + (1 - \beta(1 - G(z_{t-s}, \gamma, c))L - \beta^* G(z_{t-s}, \gamma, c)L) v_t \quad (5)$$

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where $v_t = u_t^2 - \sigma_t^2$;$0 < d < 1$; β; β^* are the volatility dynamics parameters and $G(z_{t-s}, \gamma, c) = \dfrac{1}{1 + \exp(-\gamma(z_{t-s} - c))}$ is logistic transition function with transition variable *s* period lagged *z* where *s* is the delay parameter, and *c* is the threshold. The parameter γ determines the smoothness of change in the value of the transition function between regimes and is assumed positive for identification purposes. Again, *G*(.) characterizes the transition function and is bounded between 0 and 1. This function changes monotonically from 0 to 1 as z_{t-s} changes. If $z_{t-s} \to \infty$, *G*(.) →1, and hence the STFIGARCH(1,d,1) behaves locally like a FIGARCH(1,d,1) process with β^* parameter. When $z_{t-s} \to -\infty$, *G*(.) →0, and thus STFIGARCH(1,d,1) model reduces to FIGARCH (1,d,1) model with parameter β . If $z_{t-s} \to c$ of if γ = 0, hence *G*(.) → $1/2$ and then the dynamic of STFIGARCH (1,d,1) becomes the same as that of FIGARCH(1,d,1) model dynamic parameter $\dfrac{\beta + \beta^*}{2}$.

When $z_{t-s} \to -\infty$;*G*(.) → 0 and hence STFIGARCH(1,d,1) behaves locally like a FIGARCH (1,d,1) model with parameter β . When $z_{t-s} \to c$ or when γ = 0, then *G*(.) →*1/2* is the same as that of FIGARCH (1,d,1) model with the parameter $\dfrac{\beta + \beta^*}{2}$. The regime associated with *G*(.) = 1 can be thought to be the upper regime and the regime where *G*(.) = 0 is the lower regime. When they arranging the model (6) becomes:

$$\sigma_t^2 = \omega + (1 - \beta(1 - G(z_{t-s}, \gamma, c))\sigma_{t-1}^2 + \beta^* G(z_{t-s}, \gamma, c)\sigma_{t-1}^2 + [(1 - \beta(1 - G(z_{t-s}, \gamma, c))L + \beta^* G(z_{t-s}, \gamma, c)L)(1 - \varphi L) \quad (1 - L)^d] u_{t-1}^2 \tag{6}$$

This equation implies that the conditional variance of u_t is equal to:

$$\sigma_t^2 = \frac{\omega}{\beta(1 - G(z_{t-s}, \gamma, c))} + (1 - \frac{(1 - \varphi L) \quad (1 - L)^d}{(1 - \beta(1 - G(z_{t-s}, \gamma, c))L + \beta^* G(z_{t-s}, \gamma, c)L)}) u_t^2 \tag{7}$$

This later equation shows that infinite ARCH representation and the constant term depend on the volatility regime in a given date t. We note also that the constant term takes on values on $\psi = \dfrac{\omega}{(1 - \beta)}$ and $\psi^* = \dfrac{\omega}{(1 - \beta^*)}$ across lower regime (resp.*G*(.) = 0) and upper regime (resp.*G*(.) = 1).

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According to Kilic (2011), the conditions for non-negativity of conditional volatility process are the same as the conditions given in Conrad et al. (2006) with the autoregressive parameter replaced by $\beta; \beta^*$ or $\frac{\beta+\beta^*}{2}$ for upper, lower and middle regimes respectively (see Kilic (2011) for more details).

METHODOLOGY AND SPECIFICATION TESTS

The empirical specification procedure for STFIGARCH(1,d,1) model that follows this approach consists of the flowing steps: (1) specify the model with specification tests by testing the null hypothesis of FIGARCH (1,d,1) against the alternative STFIGARCH (2) estimate the parameters in the selected model (3) evaluate the model using diagnostic tests(for more details see Lundbergh and Teräsvirta (2002)., Kilic(2011)).

Testing linearity is defined by $H_0: \gamma = 0 \; or \; H_0': \beta^* = \beta.$ The both formulations tests are non standard because under $H_0 \; or \; H_0'$, the STFIGARCH model contains unidentified nuisance parameters (see Davies (1987)) and the asymptotic distribution of t-statistic and Wald tests is not valid. To resolve this problem, Lukkonenn et al. (1988), Gonzàlez (1998) et al. (2002) proposed to replace the transition function $G(z_{t-s}, \gamma, c)$ by its first order expansion Taylor around γ = 0, the auxiliary regression is represented by:

$$\sigma_t^2 = \omega + \tilde{\beta}\sigma_{t-1}^2 + \sigma_{t-1}^2 + \left(1 - \tilde{\beta}L - (1-\varphi L) \;\; (1-L)^d\right)u_t^2 + \delta \, z_{t-s}v_{t-1}$$

where $\tilde{\beta} = \beta - c\lambda\frac{\gamma}{4}$, $\delta = \lambda\frac{\gamma}{4}$, and $v_{t-1} = u_t^2 - \sigma_t^2$ where $\lambda = \beta^*\text{-}\beta \neq 0$.

Hence, the null hypothesis becomes H_0': δ = 0. The third -order expansion Taylor around γ = 0 is represented by:

$$\sigma_t^2 = \sigma_t^2 = \omega + \tilde{\beta}\sigma_{t-1}^2 + \sigma_{t-1}^2 + \left(1 - \tilde{\beta}L - (1-\varphi L) \;\; (1-L)^d\right)u_t^2 + \delta_1 z_{t-s}v_{t-1} + \delta_2 z_{t-s}^2 \;\; v_{t-1} + \delta_3 z_{t-s}^3 \;\; v_{t-1} \quad (8)$$

Again specification test can be carried by testing H_0'': δ =δ1 =δ2 = 0 in the third order Taylor expansion. As Lundbergh and Teràsvirta (2002), Kilic(2011), we use the Wald-test statistic noted W_1, W_2 which has an asymptotic χ2 distribution with one and three degrees of freedom under H_0' and H_0'' respectively.

Estimation

For a more detailed discussions on parameter estimation in the context of regime-switching models, we refer to Hagerud (1997), Gonzales-Rivera (1998) and Meitz and Saikkonen(2008) for LSTGARCH model, to Lundbergh and Teräsvirta(2002) for STAR-LSTGARCH model and Kilic (2011) for the STFIGARCH model. The parameters can conveniently be estimated by the method of QMLE where the log-likelihood is numerically maximized with respect to the vector of parameters of LSTGARCH model, $\upsilon = (\mu; d; \omega; \beta\ ; \beta^{*}; \phi\ ; \gamma\ ; \nu\ )$ where ν is the degree of freedom parameter under the student's t distribution. The asymptotic distribution of the QMLE is:

$$T^{\frac{1}{2}} = (\hat{\vartheta} - \vartheta_0)(0, A(\vartheta_0)^{-1}B(\vartheta_0)A(\vartheta_0)^{-1}) \quad (9)$$

where T is the sample size, ϑ_0 is the true value of the vector of parameters, $A(\vartheta_0)$ is the Hessian and $B(\vartheta_0)$ is the outer product of gradient evaluated at the true parameter values.

DATA AND RESULTS

In this paper, we consider major stock market indexes of developed countries, France, Germany, Japan, the UK and the US, on the one hand, and stock market indexes of 6 selected emerging markets, on the other hand. The stock indexes considered are the CAC40 (Paris), DAX100 (Frankfurt), Nikkei225 (Japan), FTSE100 (UK), the DJIA (USA), TWII (TAIWAN), HSI(Hong Kong), BVSP(Brazil), FTSII (India),VNI(Vietnam) and KOSPI(Korea).The time span studied is 04/01/2000- 28/01/2015, except for VNI where the period is 28/07/2000-12/02/2015. All data series are drawn from Datastream base.

Table 1: Summary statistics

Series	n	Mean	Var	Skew	Kur	JB	Arch(1)	Arch(5)	Q(20)	Q(50)	Qs(20)	Qs(50)
DJIA	3913	0.0002	1.486	1.606	4.263	10460*	121.97*	827.94*	50.95*	93.5*	2186.3*	3706.9*
CAC	3987	0.0002	0.000	1.626	4.299	3455.1*	144.98*	622.49*	66.62*	120.42*	2041*	3425*
DAX	3964	0.0002	0.000	1.730	5.061	2680.2*	120.046*	620.58*	51.92*	92.73*	2801*	4896.5*
FTSE	3986	0.0002	0.000	1.696	4.626	6111.1*	218.5*	785.95*	75.29*	90.83*	2861*	4552*
Nikkei	3711	0.0015	2.422	0.413	9.160	5971.6*	268.13*	785.95*	22.28*	64.81*	3820*	4431*
HSI	3160	0.0002	0.000	5.863	79.729	510.3.1*	163.52*	323.37*	119.01*	231.69*	728*	998.96*
TWI	3728	0.0007	2.113	-0.23	6.008	1441.4*	97.345*	1487.45*	59.9*	122.27*	1103.8*	1820.4*
FTSII	3728	0.0062	1.466	-0.26	8.077	4046.7*	163.52*	438.45*	50.75*	92.5*	3171.9*	4419.6*
BVSP	3728	-0.029	3.411	0.094	6.810	2260*	84.07*	650.71*	50.95*	933.92*	3706.9*	5095.7*

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VNI	**3476**	**0.0508**	**2.636**	**-0.24**	**5.524**	**958.57***	**1226.6***	**362.42***	**455.17***	**526.5***	**722***	**1177.9***
KOSPI	**3718**	**0.0002**	**0.000**	**1.704**	**5.272**	**5267.2***	**115.549***	**525.55***	**25.07****	**72.4***	**1166***	**2749.3***

*, ** denote significance at 1% and 5% confidence level, respectively. JB is the value of Jarque and Bera statistic of the return series. The ARCH (1) and ARCH (5) are the Engle (1982) test for conditional heteroscedasticity applied to standardized residuals. The *Q*(20) and *Q*2(20)are the Ljung-Box test statistics for the return and squared return series for up to 20th order serial correlation, re- respectively.* indicate rejection at the 1 percent.

According to the descriptive statistics in Table 1 and normality test, all indices are skewed and have a leptokurtic distribution in view of significant excess kurtosis and the Jarque bera test confirms that the normal assumption is rejected. The results of independence tests hypothesis and non ARCH effect of Engle (1982), the null hypothesis for non autocorrelation and non heteroscedasticity are rejected for different lags. The p-values of W_1, W_2 tests are reported in Table 2. The results reveal strong evidence in favor of STFIGARCH model for all series, except for CAC and TWII according to W3 test. The nonlinear dynamics is consistent in both developed and emerging markets. The panels of LM tests for LSTARCH(q), QARCH(q) and ESTARCH(q) for q=5 suggest that there is strong evidence of asymmetric ARCH effects in volatility.

Table 3: Tests of Linearity

Test	**DJA**	**CAC**	**DAX**	**FTSE**	**Nikkei**	**HSI**	**TWII**	**FTSII**	**BVSP**	**VNI**	**KOSPI**
W1	**52.89**	**11.15**	**14.93**	**23.83**	**21.60**	**5.78**	**52.21**	**14.13**	**14.37**	**52.21**	**127.11**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.01)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
W2	**75.31**	**13.03**	**150.55**	**46.71**	**16.62**	**25.52**	**6.18**	**6.81**	**809.9**	**15.17**	**2.932**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.07)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.402)**
LSTARCH	**722.45**	**537.08**	**147.32**	**910.45**	**887.4**	**839.52**	**290.09**	**650.78**	**805.73**	**123.13**	**358.10**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
QARCH(q)	**644.86**	**558.91**	**182.10**	**979.66**	**954.70**	**957.00**	**957.00**	**725.96**	**707.98**	**150.11**	**521.89**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
ESTARCH(q)	**622.42**	**497.96**	**182.96**	**858.06**	**961.38**	**937.90**	**451.044**	**693.28**	**3704.83**	**151.20**	**248.16**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**

W1, W2 are the robust Wald tests based on the first and third Taylor expansion of the STFIGARCH model around $\gamma = 0$.The numbers inparenthesis are p-value of the standard variant of the LM test for LSTARCH(q), QARCH(q) and ESTARCH(q) for q=5 applied to stock index returns.

The results in Table 3 for the three models suggest that our volatility series exhibit a high degree of long-memory and an asymmetric relationship with positive and negative returns. The STFIGARCH model performs better than the FIGARCH and LSTGARCH model except the CAC 40 and FTSII where the

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FIGARCH provides the best-fit model. We note in particular that the memory effect is more present than the asymmetry effect. But, LSTGARCH is the less successful model for all series. Results for %Δψ show a difference in the constant term across outer regimes of volatility for the majority of series. This difference is more striking for emerging equity except BVSP and VNI. This difference might be associated with the link between volatility and news information and documents the inherent dynamic of market participants.

The estimation results and summary diagnostic statistic for three models are reported in Tables 4, 5 and 6 for developed and emerging stock indexes respectively. Parameters estimates indicate the introduction of nonlinearity does not reduce the value of *d* except for DAX. The estimated threshold values are between (−5% and 7%). However, the speed parameter is significant and shows that the transition between two regimes is faster for emerging markets than developed markets. Although, emerging markets have some similarities in volatility behavior, they have their own special characteristics which are different over the countries. We also note that the weakness of emerging markets conditions and business environment lead to potential vulnerabilities to negative news. In lower regime, the coefficient β is not significant for most series. This suggests that the dynamic could follow a random walk. To a negative shock, the operators of emerging are more sensitive than those in developed market and emerging markets may collapse much more abruptly. But, in the higher regime, we observe the mean-reverting phenomenon and we note, in particular, a significant dynamic of FIGARCH type. The vulnerability of emerging market is coupled with the size of market and the direct and indirect barriers which leads less heterogeneous operators behavioral. This lack of diversification opportunities for both local and foreign investors influence investment decisions related to assets allocations and affect the equity volatility which cause a quick transition.
Concerning developed market, we observe a smooth transition between a two significant regimes (β^* and β are significant). This result might be attributed to higher dispersion beliefs to news which could explain the asymmetry phenomena. In fully integrated market with higher diversification opportunities, traders acquire same information set but they receive it and react to news in a sequential random manner. In others words, the information signal is observed by each trader but not simultaneously. After a new signal, the aggregation of heterogeneous behavior follows a sequential way which explains the smoothing in the mean reversion of the price towards equilibrium and the choice of the threshold model.

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Table 3: Parameters estimates for LSTGARCH models for developed and emerging stock returns

Series	ω	μ	β	α	α'	γ	υ	LLK	AIC
DJIA	0.084	0.0127	0.888	0.1079	0.0037	5.00	5.59		
	(0.012)	(0.003)	(0.012)	(0.032)	(0.062)	(0.246)	(0.881)	-2738.3	5492.6
CAC	0.090	0.0196	0.9053	0.0851	0.001	5.00	7.03		
	(0.0165)	(0.0058)	(0.0138)	(0.0104)	(0.0005)	(0.1779)	(3.237)	-5925.2	11866
DAX	-0.0910	0.0262	0.889	0.104	0.001	3.01	5.808		
	(0.029)	(0.012)	(0.024)	(0.014)	(0.0006)	(0.092)	(2.1399)	-2333.9	4683.7
FTSE	0.0426	0.0136	0.894	0.0473	0.0946	6.00	12.127		
	(0.0138)	(0.0037)	(0.0126)	(0.0251)	(0.0488)	(3.0195)	(2.133)	-5355.3	10727
Nikkei	0.0709	0.0418	0.8837	0.0742	0.0488	3.0195	9.523		
	(0.0211)	(0.0128)	(0.0145)	(0.0149)	(0.031)	(2.300)	(1.65)	-5645.4	11313
HSI	0.0536	0.0234	0.9266	0.0289	0.0578	1.356	5.502		
	(0.0183)	(0.007)	(0.010)	(0.0182)	(0.0342)	(0.589)	(0..613)	-6160.4	12337
TWI	0.0647	0.0059	0.9774	0.0537	0.0010	5.6	6.864		
	(0.0017)	(0.0027)	(0.0081)	(0.0076)	(0.0004)	(0.2966)	(1.3444)	-6048	12121
BVSP	-0.0676	0.0661	0.9046	0.0477	0.0546	0.500	15.772		
	(0.0246)	(0.0173)	(0.0121)	(0.0855)	(0.1699)	(1.987)	(3.589)	-7210.6	14443
FTSII	0.0410	0.0088	0.9123	0.0404	0.0808	1.437	9.4467		
	(0.0132)	(0.0028)	(0.0116)	(0.0167)	(0.0298)	(0.838)	(1.4117)	-5248	10518
VNI	-24	0.0275	0.765	0.222	0.0257	6.6745	11.2554		
	(0.0038)	(0.0102)	(0.0264)	(0.0242)	(0.0186)	(6.667)	(1.7558)	-5635.1	11361
KOSPI	0.0719	0.0121	0.9248	0.0532	0.0345	2.8144	7.1499		
	(0.0178)	(0.0041)	(0.0109)	(0.0134)	(0.0134)	(1.8127)	(0.888)	-6332.7	12685

Llk is the maximized logliklihood value of each model, AIC is The Akaike information criterion.

Despite of the higher integration of the emerging markets with those of developed countries, the findings suggest that the volatility behavior and degree of efficiency in emerging markets is so different from those of developed markets (Jayasuriya et al., 2005; Brooks, 2007; Mollah et al., 2009). Our results corroborate these observations. We note, in particular, that emerging stock markets may collapse much more suddenly and recover more slowly than the developed stock markets. Hence, although emerging markets are increasingly integrated in international markets and assets are increasingly priced in a way that does not differentiate emerging assets from developed ones; the higher volatility of emerging markets has consistently been proven.

The goodness of fit applied to standardized residuals and standardized squared residuals indicate that our selected STFIGARCH and FIGARCH models are correctly specified because the hypothesis of no autocorrelation and no

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remaining ARCH effects cannot be rejected in almost all cases. However, in the case of the LSTGARCH model, the results are different and show evidence of remaining ARCH effects in returns and serial correlation of squared returns, respectively. This indicates the superiority of the STFIGARCH model in representing stylized facts in volatility dynamic.

The estimated values of Hurst-Mandelbrot Classical *R/S* statistic suggest that the null hypothesis of no long-range dependence in case of STFIGARCH and FIGARCH models for all indices could not be rejected at a generally acceptable level of significance as estimated values of the statistic fall within the acceptance region. However, for LSTGARCH, the null hypothesis of the same test is rejected at 1% level of significance. The critical values of the statistic are obtained from Lo (table II, 1991). This clearly indicates that again the STFIGARCH model out performs the LSTGARCH. We also computed Lo' statistic since Classical *R/S* statistic is sensitive to short range dependence and may be biased in the case of short-range dependence. The Lo statistic displayed in Table 6 also shows that the null hypothesis of no long-range dependence in case of LSTGARCH model for all indices could not be rejected at a generally acceptable level of significance.

Table 4: Estimation parameters of FIGARCH and STFIGARCH models for daily Developed stock returns

	μ	ϕ	ω	β	β *	d	c	γ	υ	%Δψ	llk	AIC
DJA	0.0635	0.2454	0.01	0.713		0.781			5.520		-2733.8	5483.5
	(0.01)	(0.0103)	(0.257)	(0.0031)		(0.0287)			(0.03563)			
	0.0620	0.1042	0.0100	0.7433	0.7531	0.743	3.9487	88.8116	3.0000	13.2	-2727.7	5477.5
	(0.0127)	(0.0151)	(0.0024)	(0.0280)	(0.1014)	(0.0352)	(0.1031)	(23.5247)	(0.0494)			
CAC40	0.0902	0.0292	0.1899	0.7049		0.6007			6.9688		-5924.5	11865
	(0.0159)	(0.0104)	(0.0449)	(0.0814)		(0.1021)			(0.7384)			
	0.0947	0.1917	0.0962	0.8000	0.7002	0.7407	-0.3290	6.7055	3.0000	10.00	-5989.3	12001
	(0.0164)	(0.0966)	(0.0703)	(0.1442)	(0.1367)	(0.1873)	(0.2237)	(6.9019)	(0.0662)			
DAX	-0.0877	0.0392	0.0100	0.7710		0.7846			6.0082		-2327.5	46710
	(0.3269)	(0.0181)	(0.2408)	(0.0630)		(0.0657)			(0.4289)			
	0.0803	0.0369	0.0261	0.5009	0.6475	0.6214	-2.0437	3.7512	7.0000	29.26	-2326.8	4669.6
	(0.0180)	(0.0150)	(0.0304)	(0.1002)	(0.0792)	(0.0869)	(1.0402)	(2.0242)	(0.521)			
FTSE	0.0444	0.0225	0.0805	0.5640		0.5537			12.1821		-5344.2	10704
	(0.0137)	(0.0083)	(0.0485)	(0.0657)		(0.0586)			(2.1739)			

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	0.0496	**0.0531**	**0.0608**	**0.6039**	**0.6675**	**0.6067**	**6.8203**	**11.1121**	**5.0000**	**10.53**	**-5329.5**	**10681**
	(0.0137)	**(0.0103)**	**(0.0379)**	**(0.0535)**	**(0.2236)**	**(0.0511)**	**(3.2817)**	**(7.6537)**	**(0.1731)**			
Nikkei	**-0.0550**	**0.0429**	**0.0100**	**0.7773**		**0.7984**			**11.2389**		**-5393**	**10808**
	(0.0192)	**(0.0121)**	**(0.0090)**	**(0.0406)**		**(0.0503)**			**(2.1334)**			
	-0.0502	**0.3182**	**0.0100**	**0.0100**	**0.7365**	**0.7528**	**-4.5585**	**3.0610**	**3.0000**	**72.00**	**-5385.4**	**10793**

%Δψ is the estimated percentage difference in the constant term of STFIGARCH (1,d,1) model between extremes regimes(i.e.,*G*(:) = 1 and *G*(:) = 0. Llk is the maximized loglikelihood value of each model, AIC is The Akaike information criterion. as estimated value of the statistic falls within the acceptance region**.**

The results of both tests are consistent and show evidence of remaining long memory for mean and volatility in residuals series of LSTGARCH model for the selected stock markets. According to the diagnostic tests, there is substantial evidence of non asymmetric ARCH effects for STFIGARCH and FIGARCH models. Comparing the p-values for the majority of series the rejection of sign effects appear to be more important for STFIGARCH than the FIGARCH model. But, for LSTAGRCH model the test indicates remaining nonlinearity.

To see this more clearly, we plot the estimated conditional deviations from FIGARCH and STFIGARCH models with the estimated transition functions for DJIA and FTSII over the transition variable.

Table 5: Estimation parameters of FIGARCH and STFIGARCH models for daily emerging stock returns.

	μ	**ϕ**	**ω**	**β**	β*	**d**	**c**	**γ**	**υ**	**%Δψ**	**llk**	**AIC**
HSI	**0.0532**	**0.0233**	**0.1440**	**0.6997**		**0.5557**			**7.9402**		**-6148.1**	**12318**
	(0.0178)	**(0.0123)**	**(0.0365)**	**(0.0788)**		**(0.0911)**			**(0.9730)**			
	0.0512	**0.1472**	**0.1054**	**0.0100**	**0.8000**	**0.6946**	**-4.9231**	**4.2980**	**3.0000**	**70**	**-6145.2**	**11231.2**
	(0.0175)	**(0.0433)**	**(0.0495)**	**(0.0149)**	**(0.0560)**	**(0.0785)**	**(0.2628)**	**(2.199)**	**(0.0538)**			
TWII	**0.0690**	**0.0228**	**0.1518**	**0.6409**		**0.4982**			**7.0786**		**-6041**	**12098**
	(0.0165)	**(0.0122)**	**(0.0387)**	**(0.0797)**		**(0.0722)**			**(0.7595)**			
	0.0695	**0.0294**	**0.1421**	**0.6568**	**0.0100**	**0.5169**	**5.6478**	**12.9146**	**6.0000**	**98**	**-6038.3**	**12099**
	(0.0164)	**(0.0121)**	**(0.0336)**	**(0.0758)**	**(0.3764)**	**(0.0737)**	**(0.0914)**	**(8.3075)**	**(0.4226)**			
FTSII	**0.0453**	**0.1428**	**0.0143**	**0.6463**		**0.5553**			**9.1624**		**-5247.6**	**10511**
	(0.0131)	**(0.0418)**	**(0.0066)**	**(0.0865)**		**(0.0893)**			**(1.2542)**			
	0.0469	**0.0193**	**0.1458**	**0.6575**	**0.7138**	**0.5680**	**4.2682**	**95.7495**	**7.0000**	**8.5**	**-5240.9**	**10504**
	(0.0129)	**(0.0070)**	**(0.0422)**	**(0.0810)**	**(0.1420)**	**(0.0841)**	**(0.0203)**	**(45.3085)**	**(0.4902)**			
BVSP	**-0.0656**	**0.1075**	**0.1010**	**0.5581**		**0.4929**			**14.5208**		**-7204.2**	**14430**
	(0.0236)	**(0.0398)**	**(0.033)**	**(0.0857)**		**(0.0917)**			**(3.1351)**			
	-0.0661	**0.0994**	**0.1157**	**0.5925**	**0.6115**	**0.4958**	**5.8282**	**72.1189**	**14.6820**	**3.2**	**-7203.8**	**14430**

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	(0.0257)	**(0.0327)**	**(0.0424)**	**(0.0869)**	**(0.1899)**	**(0.0935)**	**(0.1769)**	**(34.6475)**	**(3.1743)**			
VNI	**0.0004**	**0.6556**	**0.0182**	**0.5184**		**0.1722**			**11.5188**		**-5620.4**	**11263**
	(0.0014)	**(0.2711)**	**(0.0134)**	**(0.5475)**		**(0.2729)**			**(1.8595)**			
	0.0105	**0.1769**	**0.1110**	**0.0100**	**0.6305**	**0.7779**	**-2.6364**	**50.0000**	**3.0000**	**53.05**	**-5812**	**11646**
	(0.0242)	**(0.0554)**	**(0.0612)**	**(0.0239)**	**(0.0983)**	**(0.0666)**	**(0.0324)**	**(32.0240)**	**(0.0378)**			
KOSPI	**0.0763**	**0.0250**	**0.1226**	**0.5919**		**0.4899**			**7.4941**		**-6319.9**	**12656**
	(0.0177)	**(0.0133)**	**(0.0367)**	**(0.0737)**		**(0.0665)**			**(0.8824)**			
	-0.0801	**0.0476**	**0.0100**	**0.4043**	**0.7761**	**0.7661**	**-3.9791**	**38.3266**	**5.0000**	**91.9**	**-6313.8**	**12650**
	(0.0180)	**(0.0136)**	**(0.0148)**	**(0.2116)**	**(0.0502)**	**(0.0564)**	**(0.0665)**	**(17.8243)**	**(0.2439)**			

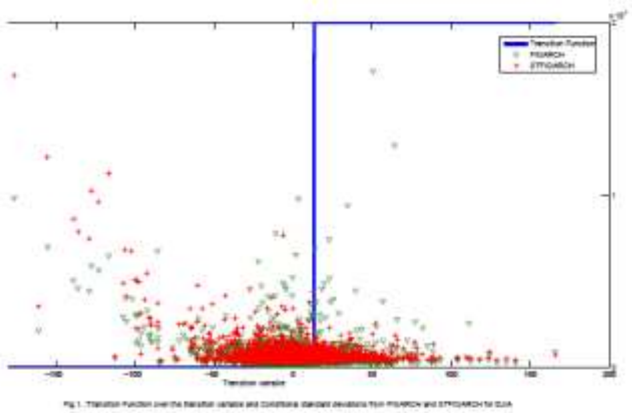

Figure.1: Transition Function over the transition variable and Conditional standard deviations from FIGARCH and STFIGARCH for DJIA

For DJIA, Figure 1 reveals that volatility changes smoothly between two outer regimes one with low volatility and the second with higher volatility. It can be seen that for large negative shocks, STFIGARCH model produces larger conditional volatility more than positive shocks with same size (leverage effect). For small shocks, we observe another kind of asymmetry, when the news is within the neighborhood of the thresholds the increase of the conditional volatility is stronger than if absolute values of news are larger than the threshold. We also note that the outer regimes are characterized by different dynamic of FIGARCH type. But on the central regime very close to the threshold, we notice a random walk dynamic where the shocks are persistent. For FTSII, the dynamics of the conditional variance is independent of the sign of past news.

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Figure 2 allows us to highlight the size effect of shocks where small and big shocks have separate effects. In this case, the ESTFIGARCH model is probably more appropriate. Standard deviations for three models are displayed in Figure 3. Some remarks can be observed. First, for STFIGARCH and STGARCH model, it is clear that the response of conditional volatility to large negative shocks is larger than those positive shocks with the same size.

Second, the STFIGARCH model produces larger conditional volatility than STGARCH for the same shock. This suggests that the STFIGARCH captures better the nonlinearity in DJIA series. For FTSII, the results are less clear.

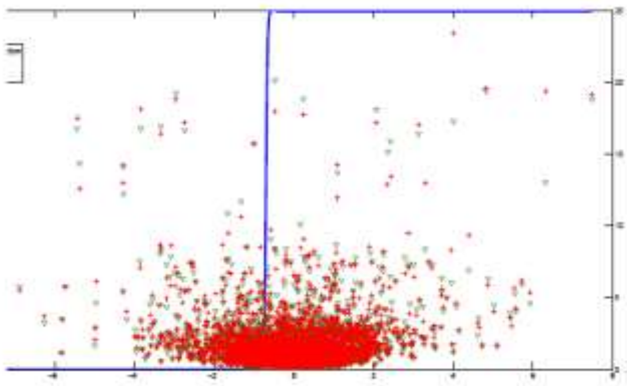

Figure 2: Transition function over the transition variable and conditional volatility from FIGARCH

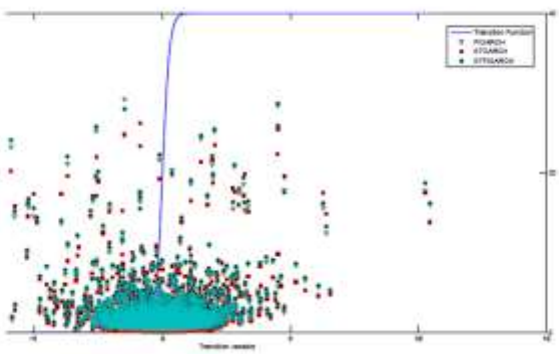

Figure 3: Transition function over the transition variable and Conditional standard deviations from FIGARCH, STGARCH and STFIGARCH for DJIA

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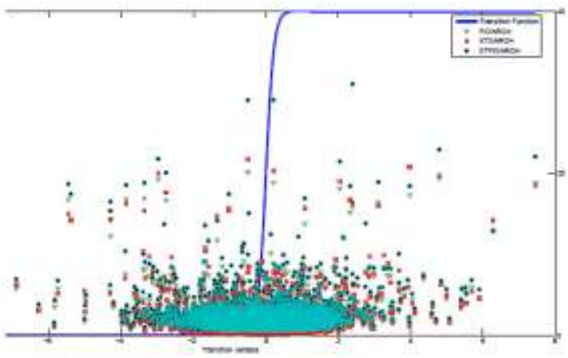

Figure 4: Transition function over the transition variable and Conditional volatility from FIGARCH, STGARCH and STFIGARCH for FTSII

Table 6: Evaluating tests for LSTGARCH, FIGARCH, LSTFIGARCH.

Stock	DJIA	CAC	DAX	FTSE	NIKKEI	HSI	TWII	FTSII	BVSP	VNI	KOSPI
STFIGARCH											
LM(Q(20))	0.037	0.2815	0.67	0.273	0.9269	0.67	0.0147	0.499	0.205	0.00	0.593
LM(Q^2(20)	0.00	0.00	0.00	0.00	0.00	0.242	0.031	0.206	0.709	0.427	0.799
ARCH(1)	0.18	0.0143	0.79	0.000	0.000	0.005	0.199	0.145	0.42	0.62	0.715
R/S statistic	1.1137	1.169	1.3792	1.1206	1.3579	1.596	1.288	1.774	1.79	2.31	1.741
R/S modified (Lo(1991))	1.1411	1.869	1.3857	1.1368	1.3559	1.586	1.248	1.7538	1.586	2.053	1.711
R/S ^{2} statistic	1.328	1.448	1.079	1.287	1.137	1.26	1.045	1.68	1.057	1.865	0.922
R/S^2 modified (Lo(1991))	1.343	1.443	1.074	1.34	1.141	1.29	1.027	1.69	1.053	1.857	0.971
LSTGARCH											
LM(Q(20))	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LM(Q^2(20))	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ARCH(1)	0.00	0.00	0.00	0.00	0.001	0.00	0.00	0.00	0.00	0.00	0.00
Long memory tests											
R/S statistic	6.467	3.586	6.95	3.24	6.075	7.457	6.224	7.086	6.075	4.738	7.457
R/S modified (Lo(1991))	5.97	3.495	6.49	3.23	5.57	8.94	5.832	6.48	5.57	4.692	8.937
R/S^2 $statistic	5.209	5.55	8.039	4.447	8.0397	4.494	7.091	6.661	6.661	6.245	9.091
R/S^2 modified(Lo(1991))	5.394	5.05	7.35	4.238	7.357	4.381	6.528	6.019	6.019	6.027	7.489
FIGARCH											
LM(Q(20))	0.037	0.00	0.554	0.506	0.889	0.780	0.0018	0.1948	0.207	0.00	0.00
LM(Q^2(20))	0.736	0.836	0.864	0.93	0.7058	0.712	0.0256	0.134	0.674	0.418	0.00

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ARCH(1)	**0.477**	**0.507**	**0.74**	**0.35**	**0.094**	**0.196**	**0.029**	**0.727**	**0.356**	**0.321**	**0.00**
Long memory											
R/S statistic	**0.971**	**1.918**	**0.865**	**1.316**	**1.257**	**1.551**	**1.266**	**1.815**	**1.78**	**2.273**	**0.8912**
R/S modified (Lo(1991))	**1.005**	**1.8365**	**0.858**	**1.337**	**1.277**	**1.528**	**1.225**	**1.79**	**1.79**	**2.018**	**0.917**
R/S² $statistic (Lo(1991))	**1.335**	**1.357**	**1.086**	**1.371**	**1.232**	**1.38**	**1.073**	**1.61**	**1.065**	**1.93**	**0.921**
R/S ² modified (Lo(1991))	**1.35**	**1.082**	**1.361**	**1.216**	**1.365**	**1.055**	**1.605**	**1.057**	**1.91**	**0.923**	
Sign test											
STFIGARCH	**0.461**	**0.248**	**0.361**	**0.733**	**0.149**	**0.646**	**0.18**	**0.768**	**0.491**	**0.998**	**0.99**
LSTGARCH	**0.015**	**0.002**	**0.004**	**0.005**	**0.00**	**0.001**	**0.132**	**0.578**	**0.000**	**0.000**	**0.00**
FIGARCH	**0.232**	**0.001**	**0.24**	**0.661**	**0.092**	**0.623**	**0.149**	**0.718**	**0.443**	**0.899**	**0.00**

Q(20),*Q*2(20) and ARCH(1) are the p-value of the Ljung-Box test for autocorrelation with 20 lags applied to squared standardized residuals and the Engle (1982) test for conditional heteroscedasticity applied to standardized residuals.*R/S* statistic is the traditional R/S statistic and is equivalent to the Lo (1991) modified *R=S* statistic where q is equal to zero.*R/S* modified is calculated (Lo(1991) statistics) for q=1. Note: Critical values: 10%level of significance [0*:*861*;* 1*:*747] 5%level of significance [0*:*809*;* 1*:*862] 1%level of significance [0*:*721*;* 2*:*098].For the sign test, the numbers in parenthesis are the p-value of diagnostic test.

We note that if shocks approach the threshold level, volatility tends to increase but if shocks are large in absolute value, the conditional volatility would be lower. The comparison of three models reveals again that STFIGARCH model capture better this type of asymmetry.

Table 7: Forecast Evaluation of STFIGARCH model as compared to FIGARCH and LSTGARCHmodel

	DJA	**CAC**	**DAX**	**FTSE**	**Nikkei**	**HSI**	**TWII**	**FTSII**	**BVSP**	**VNI**	**KOSPI**
MSE(F)	**1.039**	**0.999**	**1.001**	**1.054**	**0.993**	**1.169**	**1.00**	**0.997**	**1.01**	**1.02**	**1.001**
MSEP(F)	**0.0993**	**1.055**	**1.075**	**1.04**	**0.77**	**1.297**	**1.014**	**1.055**	**1.046**	**1.097**	**1.002**
MAE(F)	**1.014**	**1.033**	**1.005**	**1.013**	**0.991**	**1.067**	**0.997**	**1.003**	**0.996**	**1.001**	**1.000**
MAEP(F)	**0.995**	**1.101**	**1.015**	**1.016**	**0.992**	**1.019**	**1.002**	**1.012**	**1.011**	**1.029**	**1.001**
QLIK(F)	**1.003**	**1.003**	**1.022**	**1.003**	**0.988**	**1.007**	**0.998**	**1.003**	**1.006**	**1.017**	**1.002**
DM _(F-STF)	**0.913**	**0.2075**	**0.436**	**0.922**	**0.4262**	**0.885**	**0.816**	**0.207**	**0.471**	**0.992**	**1.001**
MSE(ST)	**0.690**	**0.657**	**0.845**	**0.784**	**0.795**	**1.103**	**0.799**	**0.657**	**0.754**	**2.34**	**0.261**
MSEP(ST)	**1.533**	**0.984**	**0.757**	**2.055**	**0.261**	**0.115**	**1.602**	**0.984**	**0.206**	**2.18**	**0.998**
MAE(ST)	**0.475**	**0.520**	**0.802**	**0.567**	**0.894**	**0.903**	**0.671**	**0.520**	**0.943**	**0.0219**	**0.161**
MAEP(ST)	**1.1066**	**1.036**	**0.986**	**1.201**	**0.772**	**0.690**	**1.037**	**1.036**	**0.655**	**1.056**	**0.999**
QLIK(ST)	**0.6865**	**0.667**	**0.841**	**0.744**	**0.838**	**0.692**	**0.813**	**0.667**	**0.995**	**0.59**	**0.312**
DM_(ST-STF)	**0.0364**	**0.0345**	**0.0375**	**0.020**	**0.0158**	**0.245**	**0.002**	**0.0345**	**0.030**	**0.030**	**0.000**
SPA											

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FIGARCH	**1.001**	**1.002**	**0.379**	**1.001**	**0.434**	**1**	**0.073**	**0.372**	**0.213**	**0.230**	**1.001**
LSTGARCH	**0.000**	**0.3842**	**0.001**	**0.001**	**0.073**	**0.118**	**1**	**0.001**	**0.0216**	**1.001**	**0.000**
LSTFIGARCH	**0.089**	**0.2373**	**1**	**0.114**	**1**	**0.156**	**1.001**	**1.002**	**1.001**	**0.002**	**0.508**

The rows labeled *DMS* give p-values for the predictive accuracy test discussed in Deibold and Mariano (1995), based on squared and absolute prediction errors respectively. (F-STF),(ST-STF) mean that the STFIGARCH model is compared to FIGARCH model and LSTGARCH respectively. SPA is Superior Predictive Ability test.

The forecasting performance of the competing models is presented in Table 7. We compute 1500 one-day-ahead forecasts of that conditional volatility. We re-estimate the FIGARCH, LSTGARCH and STFIGARCH for emerging and developed stock returns in the 04/01/2011−25/02/2011 sample period and we use these estimations to obtain the one -day-ahead forecast of conditional volatility, we update our estimation each two weeks. To evaluate the forecasting performance, we compute the mean squared (MSE), the mean absolute (MAE), mean squared and absolute prediction errors (MSEP and MAEP) with true volatility measured by the squared returns. Again the results show that the STFIGARCH model outperforms the LSTGARCH model but the FIGARCH still a competing model. More precisely, we compute the *p-value* of Deibold and Mariono (1995) (DM) predictive accuracy tests and Superior Predictive Ability (SPA). The reported *p-value* conclude to the significantly difference between one day-a-head forecasts from the STFIGARCH and LSTGARCH models at either 5% or 10% significance for all series. But this difference does not significant between STFIGARCH and FIGARCH models. The reported SPA p-values clearly confirm the DM test conclusions.

CONCLUSION

The objective of this paper is to examine the effects of asymmetry and long memory properties in modeling and forecasting volatility of stock markets of five major developed markets and six selected emerging markets. We compare the estimation of FIGARCH, LSTGARCH and STFIGARCH models. The results show that conditional volatility of all series exhibits asymmetry and long memory. The STFIGARCH model is identified as the best specification for modeling conditional heteroscedasticity of the majority of series and performs well in forecasting one-day-ahead volatility. We conclude, in particular, that transition in most of emerging markets is faster than in developed ones. This result suggests that emerging stock markets over react and more abruptly to news but the recovery is more difficult than G7 stock markets.

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