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Equity markets volatility dynamics in developed and newly emerging economies: EGARCH-with-skewed-t density approach

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Abstract

We examine the volatility dynamics of four “newly” emerging and four developed stock markets using GARCH-type models and their variants and identify breaks in returns using the ICSS test proposed by Inclan and Tiao (1994). We compare MINT (Mexico, Indonesia, Nigeria and Turkey) emerging markets with those of four developed markets (France, Germany, Japan and USA) using weekly data from January 3, 1994 to March 31, 2014 and for Indonesia from July 1, 1997 to March 31, 2014. The estimates of GARCH, EGARCH (with and without breaks) and EGARCH-with-skewed-t density models are assessed to analyse the impact of variance shifts and distributional assumptions on equity market returns. Results reveal that the incorporation of variance shifts reduces the level of persistence in GARCH models. Stability and fluctuation tests suggest that returns and conditional volatilities in the stock markets have not been stable, especially during periods of financial crises. The paper concludes that EGARCH-with-skewed-t density specification exhibits improved model diagnostics compared to the standard (a)symmetric GARCH models (with Gaussian or Student's t densities) in the context of skewness, leverage and fat tails often present in financial returns.

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1 Introduction

Analysing stock returns volatility and breaks associated with significant events is attracting increased attention in the literature (see, Aggarwal *et al.*, 1999; Beltratti and Morana, 2006 and Babikir *et al.*, 2012). Since the 1980s, time-varying properties of financial returns have been investigated using conditional heteroscedasticity models and the search for a more appropriate model for the analysis of financial market dynamics has been relentless (see, Engle, 1982; Bollerslev, 1986; Granger and Ding, 1996; Rapach and Strauss, 2008; Baillie and Morana, 2009, Harvey and Sucarrat, 2014 and Salisu, 2016). In many studies, the volatility of financial returns were found to be affected significantly by sudden changes, regime shifts and variance breaks corresponding to economic, financial and political events. Such sudden changes tend to affect the degree of persistence of returns volatility. Studies by Kang *et al.* (2009) and Babikir *et al.* (2012) have highlighted how persistence–a crucial component of risk management, portfolios and derivatives pricing, is affected by breaks. Since the late 1990s, the Nigerian Stock Exchange (NSE) All-Share Index (NSEASI), rose steadily with occassional periods of high volatility with similar trends for other emerging markets (EMs). The NSEASI attained record high levels in 2006 before falling drastically in the period from 2007–2009 reflecting fluctuations in prices of listed equities, with resultant losses for investors and implications on risks in equity markets. The NSEASI which stood at 66,371.20 points in 2007 dropped by 45% in 2008 (*NSE Factbook,* 2009, 2012). In developed markets (DMs), Japan's Nikkei-225 index reached its highest value of 38,916 points on December 29, 1989 before declining to its lowest level in the 2000s and subsequently leading to sustained bear markets until the 2008 to 2009 period. In the U.S. equity market, the Standard and Poors (S&P)-500 and Dow-Jones Industrial Average (DJIA) were impacted significantly by the market crash of the late 1980s, the dot-com bubble, the 2001 recession and the global financial crisis (GFC)(2007–2009) (see, Schwert, 2002 and Engle and Rangel, 2008).

The similarity of MINT[1] (Mexico, Indonesia, Nigeria and Turkey) economies in terms of growth prospects makes their stock markets a good comparative case study for examining sudden changes or shifts in variance and volatility persistence in relation to developed markets. Additionally, Mexico, Nigeria and Indonesia are oil exporters and leading economies in their respective regions. The NSE in late 2013 had 203 listed companies with a market capitalisation of $80.8 billion while the *Bolsa Mexicana de Valores* (Mexico) with a capitalisation of $402.99 billion in early 2016 is the second largest stock exchange in Latin America. The Jakarta composite index established in 1983, had 462 listed companies reaching its all-time high of 5,155.09 points in mid-2013 (*NSE Factbook*, 2013; *Jakarta Stock Exchange Factbook*, 2013). Although many studies have examined equity market volatility of group of countries, few focused on the MINT countries *vis-à-vis* DMs as potential investment alternatives. Previous literature such as Lamoreux and Lastrapes (1990) in analysing variance shifts in GARCH models divided their sample into equally spaced, non-overlapping intervals, within which the variance might be different due to a lack of technique like the iterated cumulative sums of squares (ICSS) algorithm. This study using the ICSS approach re-examines the issues.

The recent GFC which emanated from DMs before spreading to EMs had significantly impacted on the NSE and several African and Asian financial markets. The recession in DMs and economic slowdowns in EMs, the reduced credit flows & foreign investments, and the drying up of lines of credit for banks contributed to the reduction in economic activities and to the stock markets downturn in the 2007 to 2009 period. The NSE felt the impact of global meltdown beginning in the second quarter with market capitalisation dropping from ₦12.64 trillion on May 3 to ₦6.21 trillion on December 16 before closing at ₦9.56 trillion on December 31, 2008. This decline resulted mainly from price depreciation in equities, de-listing of companies and maturing of outstanding bonds. Gripped by the urgent need for liquidity, investor sell-off caused an excess supply of stocks, which depressed most stock prices (*NSE Factbook,* 2009). Consequently, the market witnessed a paucity of fresh funds and panic divestment. The Central Bank of Nigeria (CBN) tightened liquidity in the banking sector due

[1]MINT is an acronym referring to the economies of Mexico, Indonesia, Nigeria and Turkey. The term was popularised by Jim O'Neill of Goldman Sachs who had earlier coined the term BRIC, an acronym for the economies of Brasil, Russia, China and India and subsequently BRICS with the inclusion of South Africa.

to an excess supply of stocks by investors (CBN, 2010). Other EMs considered relatively immune to contagion were equally affected. For instance, the Johannesburg Stock Exchange (JSE), lost 27% in 2008 (CBN, 2010). See, Babikir *et al.* (2012) and Leeves (2007) for similar discussions on Indonesia during the Asian financial crisis (AFC) and Alper & Yilmaz (2004) for analysis on Turkey.

This paper investigates equity market volatility with univariate GARCH models (using Student's t and skewed-Student's t densities) and compare DMs and "newly" EMs stock returns. We analyse stock market volatility and impact of the recent financial crisis by incorporating variance shifts in GARCH estimations and examine sudden changes in variance. In addition, we employ the EGARCH-with-skewed-t density model as it offers state-of-the-art specification with leverage (volatility asymmetry) and heavy-tailed skewed densities and enables richer dynamics. It equally takes into account key features of financial returns ranging from leverage (implying that volatility tends to be higher after negative returns), conditional fat-tailedness (suggesting that standardised return is more fat-tailed than the normal) to conditional skewness (i.e. standardised return is not symmetric). In the context of investment, a return distribution with positive skew often has frequent small losses and a few extreme gains while a return distribution with negative skew has frequent small gains and a few extreme losses. That is why taking these issues into account is quite crucial particularly for investors. This paper adds to the literature and contributes to debates on the impact of sudden changes in volatility on stock markets from EMs perspective *vis-à-vis* DMs. Apart from Section 1, the subsequent sections of the paper are structured as follows: Section 2 discusses related literature while Section 3 presents the iterated cumulative sums of squares (ICSS) algorithm, unit root tests in the presence of structural breaks and GARCH methodologies and their statistical properties. Section 4 describes the data, examines unit roots and presents ARCH test results while Section 5 discusses dynamics of the fitted models with their implications, and presents stability and fluctuation test results as well as the out-of-sample forecast performance of selected fitted models. Section 6 concludes.

2 Overview of Related Literature

Over the years, in both EMs and DMs, stock prices and their returns have experienced large fluctuation due to policy changes, interest-rate cuts, domestic economic and global financial events from the AFC (1997–1998), the dot-com bubble (2000) to the GFC (2007–2009), and the on-going E.U. debt crises (see, Hammoudeh and Li, 2008; Kang *et al.,* 2009, 2010, etc). Other factors associated with country specific events from the Mexican crisis, credit rating downgrades to the Bank of Japan's (BOJ) bond buying and the U.S. Federal Reserve's quantitative easing (QE) and tapering (reduction in asset purchases) programmes have impacted on stock markets and contributed to the increased research interest. The emergence of autoregressive conditional heteroscedastic (ARCH) models and many extensions from the generalised-ARCH (GARCH), exponential-GARCH (EGARCH) to stochastic volatility (SV) models have led to application to diverse areas including inflation dynamics (see, Engle, 1982 and Baillie *et al.*, 1996); exchange rates (see, Rapach and Strauss, 2008), and stock markets (see, Baillie and Morana, 2009; & Zivot, 2009).

Lastrapes (1989) examines exchange-rate volatility using ARCH model and finds a significant reduction in volatility persistence if controls for exogenously determined monetary regime shifts are incorporated into the model. In contrast, sudden volatility changes and break dates in this paper are endogenously identified using the ICSS algorithm developed by Inclán and Tiao (1994). Accordingly, Beetsma and Giuliodori (2012) and Beltratti and Morana (2006) examine the links between breaks, persistency, stock prices and the macroeconomy. Similar analysis can be found in Kasman *et al.* (2011). Aggarwal *et al.* (1999) and Kang *et al.* (2009) find that volatility persistence decreases dramatically when regime shifts are included in GARCH models. Kang *et al.* (2009) investigate sudden changes in volatility for the Japanese and Korean stock markets in the period 1986 to 2008 using the ICSS algorithm to identify variance breaks. They find that sudden volatility changes are generally associated with global financial & political events, and that controlling for these sudden changes effectively reduces persistence and long memory associated with volatility as well as helps to improve the accuracy of estimating and forecasting volatility dynamics.

Similarly, Aggarwal *et al.* (1999) investigate large sudden changes in volatility for 10 EMs in Asia and Latin America, and detected time points of sudden shifts using the ICSS test, before directly incorporating the sudden change dummies into their GARCH model. They conclude that accounting for sudden change reduces the level of persistence. Leeves (2007) analysed volatility in Indonesian stock market returns during the AFC and finds that increases in asymmetric response patterns appear to coincide with large devaluations of the rupiah over the period, followed by more general symmetric short-term volatility in the post-crisis period. Furthermore, his estimated smooth transition volatility model indicates both sign and size asymmetries during the crisis period. Returns behaviour and volatility in the NSE and other African markets have also been examined recently. Emenike (2010) investigates the behaviour of NSE stock returns volatility using the GARCH(1,1) and GJR-GARCH(1,1) models. He finds evidence of volatility clustering and the existence of leverage effects in the returns. Recently, Yaya and Gil-Alana (2014) examine persistence and asymmetry at two market phases (bull and bear phases) of the NSEASI with estimates of their fractional difference parameter used as a stability measure of the degree of persistence in the level and returns of the series. They show that the level of persistence differ between the two market phases considered. For similar analysis in the context of Markov-switching, see, King and Botha (2015).

Smith (2008) examines the ability of Lagrange multiplier (LM) and cumulative sum (CUSUM) structural break tests to detect breaks in GARCH models, and finds that when the data is Gaussian, the CUSUM and LM-based tests have excellent size, but the CUSUM tends to overreject when returns have fat tails even in large samples. Cho and Yoo (2011) analyse Korean stock market volatility during the AFC (1997–1998) and GFC (2007–2009) employing a fad model with Markov-switching heteroscedasticity. Using monthly data from 1995 to 2009, they find that transitory component volatility of stock return increased during the currency crisis, but did not rise much during the credit crisis. By estimating stock return volatility with the dollar value of the index, they find that the volatility of the transitory component was raised during both the credit and currency crises with asymmetric implications. That is, foreign investors experienced greater volatility than domestic investors in the recent financial market turmoil. Japan's current aggressive fiscal and monetary policies have led to depreciation of the yen and a significant jump in the Nikkei-225 and Topix indices while Kasman *et al.* (2011) find that interest and exchange-rate volatility are key determinants of conditional bank stock returns volatility in Turkey. Recently, many EM currencies including the Nigerian naira, Argentine peso and Turkish lira came under pressure falling sharply, contributing to interest rate rises.

Hammoudeh and Li (2008) examine sudden changes in volatility for Gulf area stock markets and find that most of these markets are more sensitive to major global events than to local and regional factors based on findings that, accounting for these large shifts in volatility in GARCH(1,1) model significantly reduces persistence of volatility in the stock markets. The current surge in interest on the impact of breaks on stock return volatility was influenced by the aftermath of the GFC as all the major markets became vulnerable to shocks resulting from periods of economic and financial turmoil, political instability and sudden macroeconomic occurrences. These periods are usually associated with high volatility and variance breaks. In response to these events, Harvey and Sucarrat (2014) propose a Beta-skewed-t EGARCH model with a heavy-tailed distribution. They find evidence of skeweness in conditional t density using a range of returns and showed that the model gives a better fit than the skewed-t GARCH model. Recently, Salisu (2016) employs the Beta-skew-t-EGARCH model proposed by Harvey and Sucarrat (2014) to model volatility in oil markets. He finds that the approach is more suitable than the standard (a)symmetric GARCH models when returns exhibit fat tails, leverage and skewness. Based on the findings in the literature reviewed, the key implication of ignoring breaks in volatility modelling when they do exist is parameter bias and the associated persistence overestimation. It is in this regard that the focus of this paper is on modelling sudden changes in volatility in GARCH class of models to account for this occurence and to examine the implications of distributional assumptions.

3 Methodology

3.1 The ICSS Test: Detecting Sudden Changes in Variance

The Inclán and Tiao's (1994) ICSS algorithm endogenously detects number and position of break points in variance. The algorithm assumes that a given time series displays a stationary variance over an initial period, until various events generate a break point, then the variance returns to stationarity until the next sudden change. Inclán and Tiao (IT) propose a cumulative sum of squares (CSS) statistic to test the null hypothesis of a constant unconditional variance against the alternative of a break in the unconditional variance. The test statistic is defined in Eqn.(1) as

$$IT = \sup_k |(T/2)^{0.5} D_k|, \tag{1}$$

where the centred CSS function is $D_k = (C_k/C_T) - (k/T); k = 1, ..., T$ and $C_k = \sum_{t=1}^{k} r_t^2$. The value of k that maximises $|(T/2)^{1/2} D_k|$ is the estimate of the break date (see, Inclán and Tiao, 1994; Rapach and Strauss, 2008). Although there are several tests for detecting breaks, we employ IT's test since our sample is of moderate size. An advantage of IT's test is that it is capable of detecting multiple breaks whereas the LM-type tests cannot. A disadvantage of the test is that it is only capable of detecting breaks in the unconditional level of volatility and that the statistic can be substantially oversized when the series follow dependent process (see, de Pooter and van Dijk, 2004).

3.2 Unit Root Tests with Structural Breaks

3.2.1 Zivot and Andrews Endogenous One-Break Unit Root Tests

The Zivot and Andrews (ZA)(1992) test allows for a single break (at an unknown date) in the intercept, trend and/or in both intercept and trend. Zivot and Andrews propose a data dependent algorithm to determine breakpoints (i.e. allowing the break point to be determined from the data). The ZA unit root tests with breaks in both intercept and trend are computed using Eqn.(2) below

$$y_t = c_0 + \beta t + \theta DU_t + \gamma DT_t + \alpha y_{t-1} + \sum_{i=1}^{k} d_i \Delta y_{t-i} + \varepsilon_t, \tag{2}$$

where Δy_t is the first difference of y_t, Δy_{t-i} is added to eliminate serial correlation in ε_t. The ε_t is the residual while c_0 is the intercept and $DU_t = 1$ if $t > T_B$, 0 otherwise; $DT_t = t - T_B$ if $t > T_B$, 0 otherwise. The T_B is the endogenously determined break date. The model (mixed model) allows for both a one-time change in the trend function's intercept under the alternative hypothesis and a single change in the slope of the trend function without any change in the level taking place simultaneously. The null hypothesis states that the series are integrated of order one (unit root) without structural breaks ($\alpha = 1$). The test statistic is the minimum t over all possible break dates in the sample.

3.2.2 Lee and Strazicich Unit Root Test with Structural Breaks

Lee and Strazicich (2003) propose an endogenous two-break LM unit root test using the test statistic

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1} + \sum_{i=1}^{k} \lambda_i \Delta \tilde{S}_{t-i} + \varepsilon_t, \tag{3}$$

where $\tilde{S}_t = y_t - \tilde{\psi}_x - Z_t\tilde{\delta}$ and $t = 2, 3, ..., T$ is a de-trended series, while $\tilde{\delta}$ are coefficients in the regression of Δy_t on ΔZ_t and Δ is the difference operator. The $\tilde{\psi}_x$ which is the restricted maximum likelihood estimator (MLE) of $\psi_x (\equiv \psi + X_0)$ is given by $y_1 - Z_1\tilde{\delta}$ while y_1 and Z_1 are the first observations of y_t and Z_t respectively. The $\Delta\tilde{S}_{t-i}, i = 1, ..., k$ terms are included as necessary to correct for serial correlation. The unit root null hypothesis is described by $\phi = 0$ and the LM test statistics are given by $\tilde{\rho} = T\tilde{\phi}$, where $\tilde{\tau} = t$–statistic for the null hypothesis $\phi = 0$. To endogenously determine the break points (T_{B_j}), the minimum LM unit root test uses a grid search given by $LM_\rho = \inf_\lambda \tilde{\rho}(\tilde{\lambda})$ and $LM_\tau = \inf_\lambda \tilde{\tau}(\tilde{\lambda})$, where $\lambda = T_b/T$ and T is the sample size. The breakpoints are determined where the test statistic is minimised. We use a trimming region of (0.15T, 0.85T) to eliminate endpoints.

3.3 Generalised Autoregressive Conditional Heteroscedasticity (GARCH) Models

Engle's (1982) ARCH specification is given below, where $r_t = \omega + \varepsilon_t$ is the conditional mean and ε_t is the error term. The conditional variance is $\sigma_t^2 = var(\varepsilon_t|\mathcal{F}_{t-1})$ where $\mathcal{F}_{t-1}$ is the information set. The ARCH model is given by $\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2, \varepsilon_t = z_t\sigma_t, z_t \sim i.i.d.(0,1)$, where $\alpha_0 > 0, \alpha_j \geq 0, j = 1, 2, ..., q-1$ and $\alpha_q > 0$. The mean is given by α_0, while α_j is the ARCH parameter. The parameter restrictions form a necessary and sufficient condition for a positive conditional variance. The GARCH(p,q) model proposed by Bollerslev (1986) is given in Eqn.(4) as

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{4}$$

where β_j is the GARCH parameter. A sufficient condition for the conditional variance to be positive with probability one is $\alpha_0 > 0, \alpha_j \geq 0, j = 1, 2, ..., q-1; \alpha_q > 0; \beta_j \geq 0, j = 1, ..., p-1; \beta_p > 0$. The model is specified as a function of three terms: α_0, ε_{t-j}^2 and σ_{t-j}^2. The persistence of σ_t^2 is captured by $\alpha + \beta$ and covariance stationarity requires that $\alpha + \beta < 1$, while the unconditional variance is equal to $\alpha/(1 - \sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j)$. The EGARCH model introduced by Nelson (1991) allows for asymmetric effects between positive and negative asset returns. The specification for conditional variance is

$$\log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2), \tag{5}$$

where the γ_i parameter captures asymmetry if $\gamma_i \neq 0$. An unexpected increase in the stock return (when ε_t is positive) can be thought of as the arrival of "good news" in the sense that returns are higher than expected while a negative ε_t indicates "bad news" as the return is lower than expected (Leeves, 2007). The EGARCH is covariance stationary provided $\sum_{j=1}^{p} \beta_j < 1$ (Zivot, 2009). Recent studies, e.g. Babikir *et al.* (2012) have argued that GARCH models tend to overestimate volatility persistence when regime shifts and breaks are not taken into account. We incorporate explanatory variables into the EGARCH(1,1) model represented by the Eqn.(6) as

$$\log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) + \sum_{k=1}^{n} d_k D_k, \tag{6}$$

where $D_1, ..., D_n$ are dummy variables taking a value of 1 from each point of sudden change of variance onwards and zero elsewhere. The coefficient d_k in Eqn.(6) measures the impact of the dummy variables on changes in the conditional variance of return. Thus, we estimate EGARCH(1,1) model (with(out)) dummy variables) corresponding to the sudden change points. Furthermore, the standardised skewed-Student's-t probability density function, $f(\cdot)$ is given by

$$f(\varepsilon|\xi,\nu) = \frac{bK(\nu)}{\sqrt{\sigma_t^2}} \left(1 + \frac{\zeta_t^2}{\nu - 2}\right)^{-(\nu+1)/2}, \; \nu > 2, \; \xi \in \Re, \tag{7}$$

where $K(\nu) = \frac{\Gamma[(\nu+1)/2]}{\sqrt{\pi(\nu-2)}\Gamma(\nu/2)}$, $\lambda = \tanh(\xi)$, $b = \sqrt{1 + 3\lambda a^2 - a^2}$, $\zeta_t = \frac{b\varepsilon_t + a}{1-\lambda}$ for $\varepsilon_t < -a/b$ and $\zeta_t = \frac{b\varepsilon_t + a}{1+\lambda}$ for $\varepsilon_t > -a/b$. In skewed distributions, λ is often treated as the hyperbolic tangent of an unconstrained real parameter ξ compared to their original parameterisation.

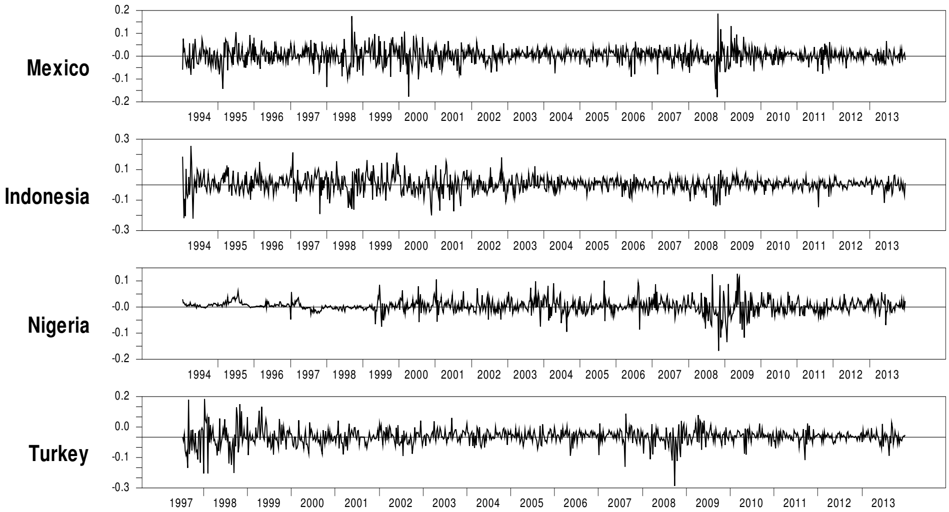
3.4 Stability and Fluctuation Tests for GARCH-type Models

Nyblom (1989) examined parameter instability in a general framework. The Nyblom's fluctuation test statistic is given by

$$S_T^{(N)} = \sum_{j=1}^{T} (\sum_{t=j}^{T} \boldsymbol{s}_t'(\hat{\boldsymbol{\Theta}}))((\hat{\sigma}^2 T)^{-1} \sum_{t=1}^{T} \boldsymbol{z}_t \boldsymbol{z}_t')^{-1} (\sum_{t=j}^{T} \boldsymbol{s}_t(\hat{\boldsymbol{\Theta}})), \tag{8}$$

where $\boldsymbol{s}_t(\hat{\boldsymbol{\Theta}}) = \hat{\sigma}^{-2} \hat{\varepsilon}_t \boldsymbol{z}_t$ is the score vector for observation t evaluated under parameter constancy. Thus, $\hat{\varepsilon}_t = \boldsymbol{y}_t - \hat{\boldsymbol{\Theta}}' \boldsymbol{z}_t$ where $\hat{\boldsymbol{\Theta}}$ is the maximum likelihood estimator (MLE) of the parameter vector based on all pairs of observations $(y_t, \boldsymbol{z}_t), t = 1, 2, ..., T$, under the constancy assumption and $\hat{\sigma}^2 = \sum_{t=1}^{T} \hat{\varepsilon}_t^2$ (see, Nyblom, 1989; Teräsvirta *et al.*, 2010).

Figure 1: **Dynamics of weekly emerging markets (MINT) returns (1994–2013)**



4 The Data

4.1 The Data and Descriptive Statistics

The data comprise weekly stock market returns for the period (January 3, 1994 to December 30, 2013) for 4 newly EMs (MINT) and 4 DMs. The stock market indices are the *Bolsa Mexicana de Valores* (Mexico), NSE-All Share Index (Nigeria), Jakarta Stock Exchange Composite Index (JSX)(Indonesia), and the Istanbul Stock Exchange Index (Turkey). For DMs, we used the CAC 40 (*Cotation Assistee en Continu*) (France), DAX (*Deutscher Aktien Index*)(Germany), Nikkei-225 (Japan) and Standard and Poors (S&P)-500 (USA) stock indices data. We used continuously compounded return due to its advantages, as it has attractive statistical properties such as stationarity and ergodicity (Campbell *et al.*, 1997 and Tsay, 2005). The weekly returns are computed as the logarithmic difference of weekly stock price index for each market: $r_t = \ln(P_t/P_{t-1}) = \ln(P_t) - \ln(P_{t-1})$, where r_t, P_t and P_{t-1} denote the index return, the stock price index at time t and stock price index at time $t-1$. The sample period includes major episodes from the AFC, the GFC to the E.U. debt crises. Weekly data are utilised to avoid the problems of non-synchronous trading among the sampled countries. Each country's returns were calculated in the local currency. Table 1 reports descriptive statistics for the stock indices returns.

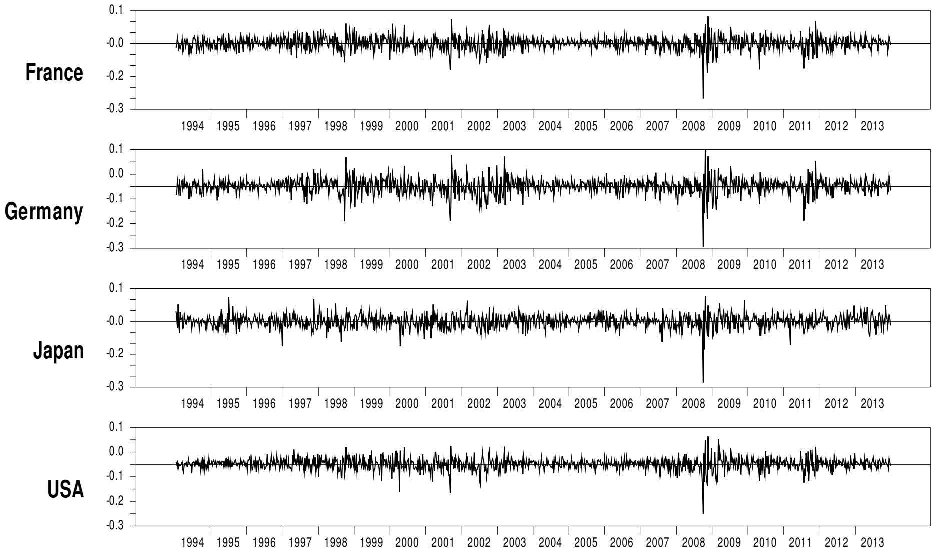
Table 1: **Descriptive Statistics for Weekly Stock Market Indices Return (1994–2013)**

Indices	**Mean**	**Median**	**Max.**	**Min.**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**
Newly Emerging Stock Markets (MINT)								
Mexico	0.0027^b	-0.0040	0.1793	-0.1858	0.0352	-0.2202^a	3.2029^a	454.2669^a
Indonesia	0.0022	-0.0042	0.2404	-0.1880	0.0410	-0.4036^a	4.6388^a	771.3479^a
Nigeria	0.0031^a	-0.0026	0.1676	-0.1277	0.0264	-0.2259^a	5.7197^a	1423.7306^a
Turkey	0.0054	0.0055	0.2546	-0.2209	0.0507	-0.1377	5.9954^a	398.8392^a
Developed Stock Markets								
Japan	-0.0003	-0.0017	0.2788	-0.1145	0.0307	-0.8969^a	8.1416^a	3000.2452^a
USA	0.0012	-0.0024	0.2008	-0.1136	0.0246	-0.7817^a	6.5237^a	1950.0953^a
Germany	0.0014	-0.0046	0.2435	-0.1494	0.0326	-0.6408^a	4.9243^a	1125.2098^a
France	0.0006	-0.0019	0.2505	-0.1243	0.0305	-0.7328^a	5.4024^a	1361.7177^a

Notes: Max., Min., and Std. Dev. represent the maximum, minimum, and standard deviation respectively. Superscripts ^{a},^{b} indicate significance at 1% and 5% levels.

Table 1 presents descriptive statistics of the eight stock market returns, and the Jarque-Bera (JB) test for normality. Results reveal that stock return volatilities are higher in EMs than in DMs in the period based on the standard deviations. The USA and France are the least volatile DMs. The sample mean of stock returns with the exception of Japan's are positive and small compared to the standard deviations. The return distributions are negatively skewed (left-tailed) for both EMs and DMs. The significant JB, kurtosis and skewness statistics for EMs indicate that returns are not normally distributed. The kurtosis (which measures thin or fat tails) is high for EMs as the value is

Figure 2: **Dynamics of weekly developed stock market returns (1994–2013)**



higher than those of two DMs, except France and Germany. These two markets have lower kurtosis than most of the EMs reported. Figures 1 and 2 show dynamics of both MINT and DM returns from 1994 to 2013 respectively. All the returns show similar behaviour during the GFC. In the period 2008 to 2009, all the returns showed higher volatility, attributed to the effect of GFC that resulted in excessive fluctuation in stock market returns. There were periods of relative quiet (early 2000s) with a period of much higher variance from 2008 to 2009. Volatility clustering associated with the return series is also quite evident.

4.2 Unit Roots and ARCH Effects Test Results

4.2.1 Unit Roots Test with Structural Break Results

Table A.1 (see Appendix) presents unit root test results with structural breaks using ZA (1992) and Lee and Strazicich (LS)(2003) tests. Results for EMs reveal that the 2007 to 2009 period which coincide with the GFC, experienced several breaks. For DMs, breaks were identified in the early 2000s and the period from 2007 to 2009. In Panel B of Table A.1, S(1) is the detrended data, while the associated t statistic is the unit root test statistic. The constant (in column 3) is the overall trend rate and the associated break dates are in columns 4 and 5 of Panel B. Furthermore, the ZA's unit root test with breaks on the intercept identified many breaks around the period 2007 to 2009. The test focuses on examining stationarity in the presence of structural breaks in mean rather than in the variance. The LS unit root test with structural break is a multiple breaks (two breaks) LM-type test, which is shown to be more powerful in finding evidence of trend stationarity than the ADF-type tests (see, Lee and Strazicich, 2003). The first break dates are in the late 1990s, while the second break dates are in the 2000s. Test results in Table A.1 reveal that the returns are stationary.

4.2.2 Testing for ARCH Effects in the Residuals

There are two main methods of testing for ARCH effects in GARCH-type analysis. The first is Engle's Lagrange multiplier (LM) test while the second is the McLeod and Li (1983) test. The ARCH tests (comprising F, χ^2 variants, and McLeod-Li tests) are given in Table A.2, while the ARCH test statistics of lags 1 to 10 are presented in Table A.3. We compute the ARCH test proposed by Engle (1982), and other variants in testing for ARCH effects. The ARCH test examines the null of "No ARCH" (hypothesis of constant conditional variance) effects. The test regresses the squared residuals on lagged squared residuals and a constant. Doan (2013) argues that the McLeod-Li test is more powerful than the general tests (e.g., BDS test) when we focus on the properties of variance, as it is specifically aimed at looking for serial dependence in the squares, while the Ljung-Box test with the principal assumption of conditional homoscedasticity tests for lack of serial correlation.

Table 2: **Sudden Changes in Volatility: Breakpoints Detected using ICSS Algorithm**

Countries	Time Period	Change points	Significant Events
Newly Emerging Stock Markets (MINT)			
Mexico	1996:01:01		The Mexican crisis.
	1998:06:01[a]		Oil price collapse; the Russian debt crisis.
	2000:07:24[a]		dot-com bubble.
	2002:09:16		Global stock price downturns.
	2005:12:26	10	
	2008:09:22		Global financial crisis triggered by subprime loans & CDS.
	2008:11:24		Bank failures, equities fell due to global financial crisis.
	2009:11:09[b]		Global financial crisis.
	2011:07:25		
	2011:12:19		
Indonesia	**1999:04:27**[a]		
	2002:12:10		
	2007:07:31		Aftermath of Chinese stock bubble of 2007.
	2007:08:14		Sub-prime mortgage crisis.
	2008:08:19	8	Global financial crisis.
	2009:05:26[a]		Global financial crisis.
	2011:10:18		
	2013:05:21		Jakarta composite (JSX) reached all-time high.
Nigeria	1995:03:27		
	1995:08:28		
	1999:05:03[a]	5	Return to democratic rule.
	2008:05:05[a]		Sub-prime mortgage crisis.
	2009:09:21[a]		Global financial crisis, banking crisis.
Turkey	1994:04:29		
	1997:09:05[a]		Asian financial crisis.
	2001:07:13		Effects of U.S. economic recession.
	2003:10:10	6	
	2009:08:07		Global financial crisis.
	2013:05:24[a]		The BIST-100 index rose to an all-time high of 93,178 points.
Developed Stock Markets			
Japan	1996:12:17		
	2002:12:03		
	2007:07:10		DJIA, S&P-500 & NASDAQ fell by more than 20%.
	2008:09:16	7	Failure of large financial institutiona leading to GFC.
	2008:10:21		Reduction in equities & commodity prices.
	2009:07:21[b]		Global financial crisis.
	2012:12:18[b]		BOJ's QE, fiscal spending (Abenomics).
USA	**1996:01:01**[a]		
	1998:07:13[a]		Russian debt crisis.
	2003:03:24		2003 Invasion of Iraq.
	2007:02:19		Subprime mortgage crisis, SSECI fell by 9%.
	2008:09:22[a]	9	Lehman Brothers bankruptcy, the global financial crisis.
	2009:03:09		Global financial crisis.
	2010:08:09		DJIA fell almost 1000 points in mid-2010.
	2011:06:20[a]		EU debt crisis.
	2011:12:19[a]		Debt crisis, major global markets plummet.
Germany	**1997:07:14**[a]		Asian financial crisis.
	2001:07:30		U.S. economic recession.
	2003:06:02[a]		effect of U.S. invasion of Iraq.
	2008:09:22[a]		Global financial crisis.
	2009:03:09[b]	8	Global financial crisis.
	2010:07:05		S&P's downgrade of Greece's ratings impact.
	2011:07:25		EU debt crisis, key global markets plummet.
	2011:12:12		EU debt crisis, global markets plummet.
France	**1997:02:24**[a]		
	2001:08:20		U.S. economic recession.
	2003:03:31[a]		invasion of Iraq.
	2007:02:19[a]	9	SSECI fell causing decline in global markets.
	2008:09:29[b]		Equities (stock) prices fell due to the global financial crisis.
	2009:03:09[b]		Global financial crisis.
	2010:07:05		
	2011:06:20[b]		EU debt crisis.
	2011:12:19[b]		EU debt crisis, global markets plummet.

Note: The periods in bold are dummies that are significant in the EGARCH(1,1) model with breaks.

5 Empirical Results and Discussions

The ICSS algorithm identifies variance breaks using a nested search procedure. By construction, these identified break dates in Table 2 are all significant at the 5% level. The ICSS statistic finds 10 breaks for Mexico, 9 breaks for the USA and France, 8 breaks for Indonesia and Germany, 7 breaks for Japan, 6 breaks for Turkey and 5 breaks for Nigeria. The break dates in bold in Table 2 are periods that are significant in the fitted EGARCH(1,1) models that is augmented with breaks at either the 1% or 5% levels respectively. From Table 2, many breaks were identified in the period 2007 to 2009. This, Kang *et al.* (2009) argue, is as a result of "recent global common information, due to increasing market integration and linkages". It suffices to note that the type of break test used will to a large extent determine the number of break dates to be identified in the variance of financial return, and in some instances the data frequency determines whether break dates will be identified or not.

Table 3: **Parameter estimates of GARCH(1,1) models for the stock market returns**

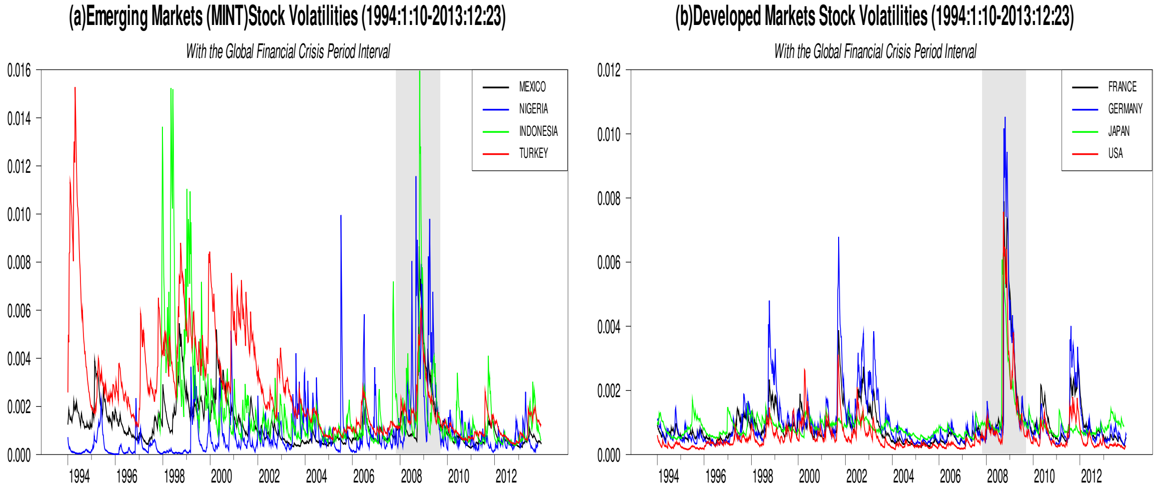
Parameter	**Mexico**	**Indonesia**	**Nigeria**	**Turkey**	**Japan**	**USA**	**Germany**	**France**
constant	0.0041^a	0.0050^a	0.0013^a	0.0047^a	0.0009	0.0028^a	0.0036^a	0.0019^a
	(0.0008)	(0.0009)	(0.0003)	(0.0012)	(0.0008)	(0.0006)	(0.0008)	(0.0007)
AR(1)	–	–	0.3675^a	0.2197^a	–	–	–	–
			(0.0346)	(0.0317)				
α_0	1.87E-5^b	8.44E-5^b	2.88E-6^b	2.10E-5	3.92E-5^b	1.96E-5^b	4.01E-5^b	2.13E-5^b
	(8.44E-6)	(3.42E-5)	(3.69E-6)	(1.33E-5)	(1.82E-5)	(9.43E-6)	(1.63E-5)	(1.01E-5)
α_1	0.0956^a	0.2207^a	0.4938^a	0.0884^a	0.0629^a	0.1439^a	0.1534^a	0.1096^a
	(0.0212)	(0.0589)	(0.0931)	(0.0228)	(0.0197)	(0.0392)	(0.0356)	(0.0251)
β	0.8906^a	0.7543^a	0.7072^a	0.9068^a	0.8929^a	0.8261^a	0.8108^a	0.8689^a
	(0.0223)	(0.0559)	(0.0316)	(0.0229)	(0.0329)	(0.0483)	(0.0429)	(0.0284)
$(\alpha_1 + \beta)$	0.9862	0.97506	1.2010	0.9952	0.9559	0.9699	0.9642	0.9785
ν	8.4349^a	4.6659^a	3.3905^a	6.1003^a	8.0693^a	8.4589^a	8.3293^a	11.7297^a
	(1.9472)	(0.7669)	(0.385)	(1.0680)	(1.5749)	(1.9313)	(1.6897)	(2.9149)
Log-lik.	2134.62	1641.75	2659.13	1800.76	2211.41	2538.71	2244.48	2276.31
AIC	-4.084	-3.883	-5.087	-3.448	-4.251	-4.863	-4.294	-4.355
SBC	-4.060	-3.855	-5.059	-3.420	-4.227	-4.839	-4.271	-4.332
L-B(Q)	20.18	29.06	154.87^a	93.26	14.74	24.97	9.95	26.02
(20)	(0.384)	(0.065)	(0.000)	(0.000)	(0.739)	(0.162)	(0.954)	(0.129)
Modified	14.90	24.76	30.93	47.00	13.20	20.58	14.50	28.21
Q (20)	(0.782)	(0.211)	(0.056)	(0.001)	(0.869)	(0.422)	(0.804)	(0.105)

Notes: Numbers in parentheses indicate standard errors. Superscripts ^{a},^{b} indicate significance levels at 1% and 5%, while log-lik, AIC, SBC, and L-B(Q) stand for log-likelihood, Akaike and Schwarz information criteria and Ljung-Box(Q) test. The AIC is defined as $-2\ln(L)/T + 2n/T$ while the SBC is given by $-2\ln(L)/T + n\ln(T)/T$ where T is the number of observations, n is the number of parameters of the fitted model and L is the likelihood function value. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

Table 3 presents result of the fitted GARCH(1,1) models. All coefficients of the key parameters are positive, satisfying the necessary and sufficient conditions given in Section 3.3. The significance of the ARCH coefficients suggests that all the stock returns exhibit ARCH effects and are significant at conventional levels. Furthermore, all the returns showed GARCH effects, indicating that their current volatility can be explained by their lagged volatility. The measure of persistence of the impact of shocks on returns $(\alpha_1 + \beta)$ shows high persistence for all the returns, even though the persistence coefficients are generally higher for EMs compared with their DM counterparts. These could be seen as implying higher risk, which may lead to higher returns. Also, results reveal that all the models, with the exception of Nigeria's stock returns model, satisfy the covariance stationary condition that $\alpha_1 + \beta < 1$. The ν for all the stock market models are greater than 2 and are significant at the 1% level, although the values for DMs are higher than those of all the EMs implying the presence of heavy tails in the innovation's distribution.

Bollerslev *et al.* (1994) argue that GARCH models with Gaussian errors are not sufficiently flexible for explaining the high kurtosis and low, slowly decaying autocorrelation features (stylised facts) in financial returns. But Malmsten and Teräsvirta (2010) have shown that the situation can be improved by replacing the normal density by a fatter-tailed density such as a Student's t or a

Figure 3: **Dynamics of emerging and developed stock market indices returns volatility**



Generalised Error Distribution (GED). The diagnostic test: the Ljung-Box(Q) statistic defined by $Q_{LB} = T(T+2)\sum_{j=1}^{T}\tau_j^2/(T-j)$ where τ_j^2, and T are the j-th autocorrelation and number of observations is provided in the last rows of Tables 3, 4 and 5 respectively (with the tests for 20th-order serial correlation in returns, shows no evidence of autocorrelation on the returns). The NSEASI exhibits autocorrelation as detected by the L-B(Q) test. In deciding on a model for the mean, we employ the Schwarz-Bayesian lag selection criteria. As a result, the criteria selected lag of 1, hence we estimate the mean equation with 1 lag for both Nigeria and Turkey. Figure 3 shows dynamics of stock returns volatility from fitted GARCH(1,1) model. Notice the upward trajectory of return volatility around the periods from 1997 to 1998 and 2007 to 2009. These are periods associated with significant global financial events. Additionally, West and Cho's modified(Q) test is also employed and it shows for Nigeria, the absence of significant serial correlation (insignificant at 5% level), although the standard Ljung-Box (Q) test reveals otherwise. However, since GARCH models are unable to capture asymmetric effects we estimate the EGARCH model with the results given in Table 4.

From Table 4, the α_1, β and γ are all significant, except the γ's of Turkey and Japan's Nikkei-225 models, although the coefficient is with the expected sign for Turkey while for Nigeria and Japan, the coefficients are positively signed. The ν's for the stock market models are higher in the EGARCH(1,1) model than in the GARCH(1,1) models in Table 3 and are significant at the 1% level, with the exception of France, which is significant at 5% level. The γ term (a measure of asymmetry of shocks) show the leverage effect (implying that bad news does increase volatility more than good news) and the coefficients are highly significant while all the signs are negative except for Nigeria. Furthermore, the log-likelihood is higher for EGARCH than for GARCH models for all the countries, while the Akaike information criterion (AIC) and the Schwarz-Bayesian criterion (SBC) are lower across all models. For the Nigerian data, a major sudden change was observed in the period from 2007 to 2009 associated with the GFC and the country's banking crisis. In terms of composition, banking stocks play a significant role in the NSE and that is why the crisis impacted negatively on the NSEASI and possibly explain the reasons behind the positive γ estimate. Recession in DMs and economic slowdowns in EMs led to reduced credit flows from remittances and foreign investments in the Nigerian economy. The drying up of lines of credit for banks had equally contributed to reduction in economic activities and to the stock market downturn in the period from 2008 to 2009 (*NSE Factbook,* 2009).

We then incorporate breaks (sudden change dummy variables) in the EGARCH models and examine their impact on volatility persistence and on conditional returns and checked robustness of the results in Table 5. The impact of breaks on the accuracy and stability of GARCH models has largely been ignored until recently. Studies such as Rapach and Strauss (2008) react to structural break by shortening the sample. An alternative approach adopted in this paper is to put shift dummies into the variance equation. Babikir *et al.* (2012) argue that failure to account for breaks can lead to sizeable upward biases in the degree of persistence in these models. Results reveal that the inclusion of signif-

Table 4: **Parameter estimates of EGARCH(1,1) models for the stock market returns**

Coeff	Mexico	Indonesia	Nigeria	Turkey	Japan	USA	Germany	France
constant	0.0036^a	0.0043^a	0.0014^a	0.0044^a	0.0005	0.0018^a	0.0026^a	0.0010^a
	(0.0009)	(0.0009)	(0.0000)	(0.0011)	(0.0008)	(0.0006)	(0.0008)	(0.0000)
AR(1)	–	–	0.3819^a	0.2229^a	–	–	–	–
			(0.0308)	(0.0282)				
α_0	-0.3647^a	-0.8878^a	–0.7945	-0.2540^a	-0.9656	-0.6117^a	-0.6669^a	-0.4544^a
	(0.1157)	(0.2442)	(0.1146)	(0.0733)	(0.7951)	(0.1775)	(0.1586)	(0.0989)
α_1	0.1899^a	0.3807^a	0.6432^a	0.1981^a	0.1714^a	0.1900^a	0.2293^a	0.1777^a
	(0.0389)	(0.0677)	(0.0628)	(0.0407)	(0.0508)	(0.0406)	(0.0402)	(0.0309)
β	0.9691^a	0.9091^a	0.9549^a	0.9834^a	0.8832^a	0.9410^a	0.9328^a	0.9571^a
	(0.0139)	(0.0326)	(0.0128)	(0.0087)	(0.1087)	(0.0204)	(0.0194)	(0.0122)
γ	-0.0779^a	-0.1128^a	0.0703^b	-0.0157	0.1116	-0.1847^a	-0.1379^a	-0.1182^a
	(0.0299)	(0.0325)	(0.0345)	(0.0193)	(0.0799)	(0.0376)	(0.0306)	(0.0283)
ν	9.129^a	4.803^a	3.613^a	6.1392^a	9.402^a	13.239^a	10.819^a	14.639^b
	(2.150)	(0.736)	(0.383)	(1.0917)	(2.779)	(4.722)	(3.798)	(7.123)
Log-lik.	2139.62	1645.51	2666.87	1800.53	2219.58	2561.80	2257.99	2291.09
AIC	-4.091	-3.890	-5.11	-3.446	-4.27	-4.91	-4.32	-4.38
SBC	-4.06	-3.86	-5.07	-3.413	-4.24	-4.88	-4.29	-4.35
L-B(Q)	20.18	29.06	154.87^a	106.66	14.74	24.97	9.95	26.02
(20)	(0.384)	(0.065)	(0.000)	(0.000)	(0.739)	(0.162)	(0.954)	(0.129)
Modified	14.90	24.76	30.93	47.00	13.20	20.58	14.50	28.21
Q (20)	(0.782)	(0.211)	(0.056)	(0.001)	(0.869)	(0.422)	(0.804)	(0.105)

Notes: Numbers in parentheses indicate standard errors. Superscripts ^{a},^{b} indicate significance levels at 1% and 5%, while log-lik, AIC, SBC, and L-B(Q) stand for log-likelihood, Akaike and Schwarz information criteria and Ljung-Box(Q) test. The AIC is defined as $-2\ln(L)/T + 2n/T$ while the SBC is given by $-2\ln(L)/T + n\ln(T)/T$ where T is the number of observations, n is the number of parameters of the fitted model and L is the likelihood value. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

icant events represented by dummy variables had an impact on stock market volatility. The inclusion of dummy variables reduces the sum of $(\alpha_1 + \beta)$ in the stock market models. Numerous studies have attempted to address questions on whether stock market volatilities behave in a different way in the aftermath of major crises and significant variance breaks. The results indicate that the GARCH terms and the persistence parameters reduced significantly due to the inclusion of variance breaks. But it seems the impact of the reduction was much greater for DM returns than for the "newly" EMs.

In addition, most of the break points (except 2001:8:20 and 2010:7:05) for France and for Turkey are significant after incorporating them into the EGARCH specification. The variance breaks that are significant in the fitted EGARCH(1,1) models which have ocassionally contributed to increasing volatility can be explained by economic, financial and political events (marked in bold face) in Table 2. For example, in the Indonesian case, the last break detected by the ICSS algorithm in May 21, 2013 is most likely associated with the Jakarta stock exchange composite index attaining an all time high value of 5,155.09 points. But, it is quite possible that this event is an outlier, and that is probably why it was not statistically significant in the fitted EGARCH model.

5.1 The Impact of Sudden Changes in Variance on Conditional Volatility

In this sub-section, we analyse the impact of sudden changes in variance on conditional volatility. Estimates from Table 5 reveal that in all cases, the persistence of shocks was significantly reduced when variance shifts were incorporated into the EGARCH models. However, the rate of decline in persistence of volatility varies across stock markets. Based on the fitted GARCH models, among all the EM returns, NSEASI experienced the largest decline in volatility persistence of 0.3207 followed by Mexico (0.1902), and the least being Indonesia (0.1675). For DMs, France's CAC-40 shows the largest decline in volatility persistence of 0.3859 which is even higher than Nigeria's, followed by USA (0.3018), Germany (0.2299) with Japan's Nikkei-225 (0.0761) experiencing the least reduction. Also, in the GARCH(1,1) model (the benchmark model) all the ν's were higher than 2, but upon the inclusion of variance shifts, the ν significantly increased for all the returns. This also highlights the trivial

Table 5: **Parameter estimates of EGARCH(1,1) with all variance shifts for returns**

Coeff	Mexico	Indonesia	Nigeria	Turkey	Japan	USA	Germany	France
constant	0.0033^a	0.0042^a	0.0021^a	0.0060^a	0.0006	0.0020^a	0.0028^a	0.0013
	(0.0007)	(0.0002)	(0.0003)	(0.0011)	(0.0008)	(0.0004)	(0.0008)	(0.0007)
α_0	-1.8150^a	-2.2560^a	-1.9660^a	-0.1865	-1.9610^a	-0.4438^b	-2.5120^a	-4.0670^a
	(0.6242)	(0.5611)	(0.4247)	(0.1730)	(0.6115)	(0.1399)	(0.6352)	(0.9562)
α_1	0.0345	0.2555^a	0.5678^a	0.1583	0.1038	0.1525	0.1859^a	0.0158
	(0.0468)	(0.0843)	(0.0652)	(0.0966)	(0.0605)	(0.0347)	(0.0544)	(0.0751)
β	0.7796^a	0.7522^a	0.7915^a	0.9899^a	0.7146^a	0.9595^a	0.6913^a	0.4771^a
	(0.0788)	(0.0578)	(0.0547)	(0.0161)	(0.0918)	(0.0159)	(0.0834)	(0.1291)
γ	-0.228^a	-0.174^a	0.084	-0.0051	-0.179^a	-0.145^a	-0.211^a	-0.229^a
	(0.0505)	(0.0600)	(0.0521)	(0.0169)	(0.0469)	(0.0337)	(0.0410)	(0.0354)
ν	14.702^a	6.354^a	5.003^a	6.4661^a	11.217^a	20.8531	117.883^b	329927^a
	(5.666)	(1.109)	(0.769)	(1.1391)	(3.501)	(11.9282)	(8.534)	(9278.94)
Log-lik.	2172.05	1667.41	2640.74	1779.38	2230.93	2579.16	2278.49	2316.01
AIC	-4.13	-3.92	-5.04	-3.392	-4.27	-4.92	-4.34	-4.41
SBC	-4.06	-3.84	-4.99	-3.335	-4.21	-4.85	-4.28	-4.35
L-B Q	20.18	29.06	154.87^a	106.66	52.47	24.97	9.95	26.02
(20)	(0.384)	(0.065)	(0.000)	(0.000)	(0.07)	(0.162)	(0.954)	(0.129)
Modified	14.90	24.76	30.93	47.00	13.20	20.58	14.50	28.21
Q (20)	(0.782)	(0.211)	(0.056)	(0.001)	(0.869)	(0.422)	(0.804)	(0.105)

Notes: Numbers in parentheses indicate the standard errors. Superscripts ^{a},^{b} indicate significance levels at 1% and 5%. Log-lik, AIC, SBC and L-B(Q) denotes log-likelihood, Akaike and Schwarz information criteria and Ljung-Box(Q). The AIC is defined as $-2\ln(L)/T + 2n/T$ while the SBC is given by $-2\ln(L)/T + n\ln(T)/T$ where T is the number of observations, n is the number of parameters of the fitted model and L is the likelihood value. For the dummy specification, we consider results from the break point test detected by the ICSS test and augment the EGARCH model with the variance shift by assigning the value of 1 for the breakpoint and 0 afterwards. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

point that inclusion of variance shifts affects the ν.

Of the 5 break dates identified by the ICSS test on Nigeria, upon their inclusion into the EGARCH(1,1) model, the periods 1999:5:03 (-0.4665) and 2008:5:05 (-0.4748) significantly impact on conditional volatility negatively while the break dates 1995:3:27 (0.0389), 1995:8:28 (0.0389) and 2009:9:21 (0.4733) exerted positive influence on volatility, with only the last date being positively significant. For Mexico, 10 break dates were identified. Among these, 1998:6:01 (-0.2359), 2005:12:26 (-0.1387), 2008:9:22 (-0.0768), and 2008:11:24 (-0.0768) have negative coefficients while 2000:7:24 (0.2403), 2002:9:16 (0.1449), 2009:11:09 (0.3080), 2011:7:25 (0.0499) and 2011:12:19 (0.0499) had positive coefficients. Among all these, only 1998, 2002 and 2009 break dates have significant coefficients. For Indonesia, 8 breaks were incorporated into the EGARCH(1,1) model. The breaks at 2007:7:31 (-0.0865), 2007:8:14 (-0.0865) and 2008:8:19 (-0.0662) had negative but statistically insignificant impact on volatility while the dates: 1999:4:27 (0.3313), 2002:12:10, 2009:5:26 (0.3560), 2011:10:18 and 2013:5:21 had positive impacts. In all these, only the 2 breaks at 1999 and 2009 are significant at 5% level. For France, 9 breaks were identified: 1997:2:24 (-0.3537), 2001:8:20 (-0.2306), 2003:3:31, 2007:2:19 (-0.4536), 2008:9:29 (-1.1867), 2009:3:09, 2010:7:05 (-0.0328), 2011:6:20 and 2011:12:19. All the coefficients are significant at conventional levels except 2001:8:20 and 2010:7:05. For Germany 8 breaks were identified and only 4 were significant at conventional levels, namely: 1997:7:14 (-0.3214), 2001:7:30 (-0.1540), 2003:6:02 (0.4391), 2008:9:22 (-0.8194), and 2009:3:09 (0.6383). Of the 9 breaks for the USA 5 were significant at 5% level namely: 1996:1:01 (-0.2671), 1998:07:13, 2008:09:22, 2011:06:20 and 2011:12:19 (0.3116). One plausible explanation why the other 4 break points were not significant is that it is possible that these events are outliers, and that is probably why they are not statistically significant in the fitted EGARCH model. The EGARCH-with-skewed-t density model along with Beta-t-skewed-EGARCH class of models are more robust to jumps and outliers than standard (a)symmetric GARCH models. Finally, 7 breaks were identified for Japan but only 2 were significant: 2009:7:21 (0.2641) and 2012:12:18 (-0.2076).

Findings based on comparison of the EGARCH models (with and without variance shifts) suggests that estimation of GARCH models without considering sudden changes may over-estimate significantly, the volatility persistence as estimating the level of persistence in volatility can help in accurately measuring how events affect stock returns volatility. The recent surge in interest on the impact of breaks on stock return volatility was influenced by the aftermath of the GFC, among other factors, as all the major markets became vulnerable to shocks resulting from periods of economic and financial turmoil, political instability and sudden macroeconomic events. These periods are usually associated with high volatility and variance breaks. Based on the above, the key implication of ignoring breaks in volatility modelling when they do exist is parameter bias and the associated persistence overestimation. It is in this regard that we examine the impact of sudden changes on volatility in GARCH models to account for this type of occurence and examine its implications.

5.2 Stability Tests for EGARCH(1,1) Model With and Without Variance Shifts

Nyblom's fluctuation test is applied in this sub-section to examine the fitted EGARCH model's stability. Doan (2013) states that "the assumption underlying the estimation of a GARCH model is that the same process generates the data throughout the range". With a converged set of MLEs, each component of the gradient of the log-likelihood sums to zero across the sample. If one of the parameters is subject to a structural break part way through the sample, one would expect to find that its gradient tends to have one sign before the break and the other sign after it, rather than having roughly equally mixed signs throughout. Nyblom's test examined the fluctuations of those partial sums of the gradient that form a Brownian bridge under the null of a stable model, and judged whether the observed fluctuations are significantly different from that. The values associated with the parameters 1, 2, 3, 4, 5 and 6 in the EGARCH model in Table 6 corresponds to the derivatives with respect to the constant (1), the variance intercept (2), and so on. The Nyblom fluctuation test on a set of series of scores compute both individual and joint test statistics (Teräsvirta *et al.*, 2010).

Table 6: **Stability tests: Nyblom fluctuation test for estimated EGARCH model**

Parameter	Mexico	Indonesia	Nigeria	Turkey	Japan	USA	Germany	France
1	0.5249^b	0.3815	1.12725	0.38329	0.4838^b	0.28131	0.11213	0.10176
	(0.030)	(0.080)	(0.000)	(0.080)	(0.040)	(0.150)	(0.510)	(0.560)
2	0.8680^a	1.2678^a	1.9602^a	0.43194	0.22242	0.19072	0.23214	0.31523
	(0.010)	(0.000)	(0.000)	(0.06)	(0.220)	(0.280)	(0.210)	(0.120)
3	0.7486^a	1.0590^a	0.8141^a	0.46996	0.2568	0.2084	0.2808	0.3924
	(0.010)	(0.000)	(0.010)	(0.050)	(0.180)	(0.240)	(0.150)	(0.080)
4	0.8559^a	1.1730^a	2.0068^a	0.43569	0.2416	0.1959	0.2213	0.3219
	(0.010)	(0.000)	(0.000)	(0.060)	(0.190)	(0.270)	(0.220)	(0.120)
5	0.1512	0.1184	0.1982	0.16952	0.2139	0.4247	0.6743	0.9553
	(0.370)	(0.480)	(0.260)	(0.032)	(0.240)	(0.060)	(0.010)	(0.000)
6	0.4402	1.0006	0.9134	0.39447	0.0592	0.1487	0.1909	0.9983
	(0.060)	(0.000)	(0.000)	(0.070)	(0.810)	(0.380)	(0.280)	(0.000)
Joint Test	1.7725^b	2.7316^a	4.6942^a	1.6815	1.4869	1.3329	1.5119	2.6486
	(0.040)	(0.000)	(0.000)	(0.100)	(0.050)	(0.170)	(0.090)	(0.000)

Note: Numbers in parentheses indicate probability values.

Table 7: **Fluctuation test for fitted EGARCH models with variance shifts**

Parameter	Mexico	Indonesia	Nigeria	Turkey	Japan	USA	Germany	France
EGARCH(1,1) with all variance shifts								
Joint Test	2.2044	1.6875	4.9276	2.3193	1.7011	1.0352	1.3487	20.1801
	(0.770)	(0.890)	(0.000)	(0.240)	(0.800)	(1.000)	(0.990)	(0.000)

Note: Numbers in parentheses indicate probability values. Only the joint test statistics are presented in Table 6.

The EGARCH(1,1) model for Mexico is largely stable and that of DMs while Indonesia and Nigeria were less stable as evidenced by noticeable large fluctuations during the GFC. Furthermore, the stock market crash reduced the market value of assets of many multinational corporations and their affiliates across the world affecting their ability to turn to equity markets for financing purposes and to leverage their mergers and acquisition activities using stock shares (UNCTAD, 2009). For Japan, the fluctuation test prefers the first eight years of the sample parameter (1994–2002) to be lower, as the derivatives are almost all negative. Thus, the fluctuation test implies that the intercept for Japan's model should be lower to fit the 1994 to 2002 period, which is very similar for Germany. Fluctuation test results for the EGARCH models with variance shifts are given in Table 6 and are largely stable with the exception of Nigeria's and France's EGARCH model. Indonesia's EGARCH model which was hitherto unstable in Table 6 became stable in Table 7 along with Mexico's.

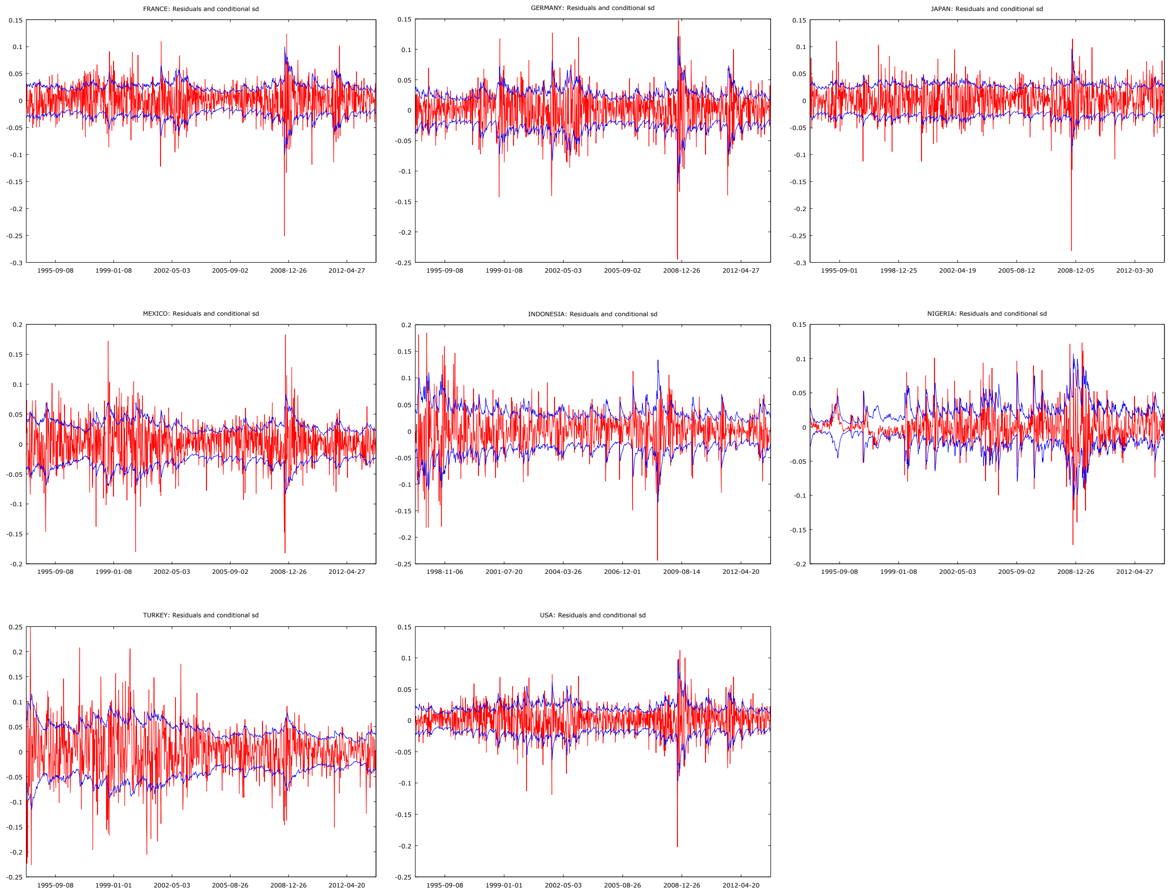
Table 8: **Parameter estimates of fitted EGARCH-with-skewed-t density models**

Coeff.	**Mexico**	**Indonesia**	**Nigeria**	**Turkey**	**Japan**	**USA**	**Germany**	**France**
constant	0.0029^a	0.0033^a	0.0018^a	0.0038^a	-8.816E-5	0.0014^c	0.0017^b	0.0007^c
	(0.0009)	(0.0012)	(0.0005)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0004)
AR(1)	–	–	0.3811^a	0.2185^a	–	–	–	
			(0.0426)	(0.0315)				
α_0	-0.3548	-0.8945^a	-0.7871^a	-0.2409^a	-0.9161	-0.6365^a	-0.7319^a	-0.4999^a
	(0.1123)	(0.2512)	(0.1262)	(0.0786)	(0.6273)	(0.1570)	(0.1653)	(0.0989)
α_1	0.1917^a	0.3822^a	0.6365^a	0.1918^a	0.1766^a	0.1932^a	0.2480^a	0.1945^a
	(0.0403)	(0.0748)	(0.0697)	(0.0418)	(0.0511)	(0.0348)	(0.0392)	(0.0274)
β	0.9706^a	0.9082^a	0.9556^a	0.9847^a	0.8905^a	0.9377^a	0.9253^a	0.9523^a
	(0.0134)	(0.0328)	(0.0129)	(0.0091)	(0.0848)	(0.0188)	(0.0206)	(0.0126)
γ	-0.0745^a	-0.1063^a	0.0684^b	-0.0154	-0.1043^c	-0.1966^a	-0.1469	-0.1247^a
	(0.0259)	(0.0373)	(0.0341)	(0.0191)	(0.0624)	(0.0357)	(0.0331)	(0.0281)
Conditional density parameters								
ν	10.3421^a	4.9732^a	3.6773^a	6.2556^a	9.5156^a	19.5439^b	13.605^b	17.3885^c
	(2.6113)	(0.7824)	(0.4798)	(1.0637)	(2.5768)	(9.6788)	(5.4718)	(8.9615)
λ	-0.1591^a	-0.1005^b	0.0865^c	-0.0752^c	-0.1567^a	-0.2315^a	-0.2922^a	-0.2349^a
	(0.0445)	(0.0492)	(0.0493)	(0.0439)	(0.0519)	(0.0497)	(0.0501)	(0.0575)
Log-lik.	2145.523	1647.688	2668.810	1801.771	2224.804	2573.192	2275.595	2300.945
AIC	-4.1007	-3.8925	-5.1123	-3.4462	-4.2732	-4.9322	-4.3501	-4.3987
SBC	-4.0675	-3.8532	-5.0709	-3.4082	-4.2398	-4.8923	-4.3169	-4.3655

Notes: Numbers in parentheses indicate standard errors. Superscripts ^{a},^{b} and ^{c} indicate significance at 1%, 5% and 10% levels while log-lik, AIC, and SBC stand for log-likelihood, Akaike and Schwarz-Bayesian information criteria respectively. The AIC is defined as $-2\ln(L)/T + 2n/T$ while the SBC is given by $-2\ln(L)/T + n\ln(T)/T$ where T is the number of observations, n is the number of parameters of the fitted model and L is the likelihood value. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

Table 8 presents estimates from fitted EGARCH-with-skewed-t density model which accounts for the key features of time-varying financial volatility: skewness, fat-tailedness and leverage. The model is characterised by its exponential specification of volatility and Harvey & Chakravarty (2008) state that its conditional variance along with Beta-t-skewed-EGARCH class of models are more robust to jumps and outliers than standard (a)symmetric GARCH models. The main coefficients to a large extent satisfy most of the conditions for EGARCH model stated earlier. The conditional density parameters are ν (degrees-of-freedom) and λ (skewness parameter). The estimated ν in the skewed-t density model in Table 8 are higher than the corresponding ν's in the EGARCH model without accounting for skewness in Table 4 and suggests the existence of considerable fat-tailed conditional t density. Theoretically, the ν must be greater than 2. In terms of the conditional skewness parameter, all the parameters are statistically significant and most with the exception of Nigeria exhibit negative skewness. In addition, results reveal that the EGARCH-with-skewed-t density model exhibits improved model diagnostics in terms of the log-likelihood statistic, Akaike and Schwarz-Bayesian information criteria. This means that taking into account skewness, asymmetry and fat tails can be crucial in modelling of the volatility of stock market returns. The results are in line with the summary statistics that showed empirical evidence for skewness and heavy tails in the returns. Thus, the EGARCH-with-skewed-t density specification is the preferred model. Figure 4 shows the plots of the residuals (red lines) and conditional standard deviation (blue lines) from the fitted EGARCH-with-skewed-t density models. Notice the upward movement of standard deviation around the 2007 to 2009 period. This trend is associated with the GFC and can be found in almost all the markets. During the GFC, correlations rose significantly among major markets as investors quickly sold risky assets due to concerns about risk. Furthermore, as central banks began implementing quantitative easing (QE) many financial assets rose in tandem.

Figure 4: **Residuals & conditional standard deviation from EGARCH-with-skewed-t model**



5.3 Out-of-Sample Forecast Performance

As highlighted in the previous sections, GARCH-type models describe movements in the conditional variance of an error term and can be used to forecast volatility (see Brooks, 2008). For a GARCH(1,1) model, the variance can be specified as

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \quad \varepsilon_t = z_t \sigma_t. \tag{9}$$

The optimal forecast of σ_{t+k}^2 given information set at time $t-1$ (denoted Ω_{t-1}) can be derived as

$$\begin{aligned} E(\sigma_{t+k}^2|\Omega_{t-1}) &= \alpha_0 + \alpha_1 E(\varepsilon_{t+k-1}^2|\Omega_{t-1}) + \beta E(\sigma_{t+k-1}^2|\Omega_{t-1}), \\ &= \alpha_0 + (\alpha_1 + \beta) E(\sigma_{t+k-1}^2|\Omega_{t-1}), \forall\, k > 0. \end{aligned} \tag{10}$$

The coefficient on the lagged term in Eqn. (10) is the sum of the coefficients on the lagged variance term and the lagged squared residuals. Eqn. (10) uses the fact that expectation of squared residuals is σ^2 by definition. From the above, multi-step forecasts can be obtained recursively. For $k = 2$,

$$\begin{aligned} E(\sigma_{t+2}^2|\Omega_{t-1}) &= \alpha_0 + \alpha_1 E(\varepsilon_{t+1}^2|\Omega_{t-1}) + \beta E(\sigma_{t+1}^2|\Omega_{t-1}), \\ &= \alpha_0 + (\alpha_1 + \beta) E(\sigma_{t+1}^2|\Omega_{t-1}). \end{aligned} \tag{11}$$

Since $E(\varepsilon_{t+1}^2|\Omega_{t-1}) = E(z_{t+1}^2 \sigma_{t+1}^2) = E(\sigma_{t+1}^2|\Omega_{t-1})$. In general, for $k \geqslant 2$,

$$E(\sigma_{t+k}^2) = \alpha_0 + (\alpha_1 + \beta) E(\sigma_{t+k-1}^2|\Omega_{t-1}),$$

$$E(\sigma_{t+k}^2) = \alpha_0 \sum_{i=0}^{k-1} (\alpha_1 + \beta)^i + (\alpha_1 + \beta)^{k-1} (\alpha_1 \varepsilon_t^2 + \beta \sigma_t^2). \tag{12}$$

The forecasting algorithm Eqn. (12) produces forecasts for the conditional variance σ^2_{t+k}. On forecast evaluation, Table 9 presents results of the mean absolute error (MAE), root mean squared error (RMSE) and Theil's inequality coefficient statistics. The MAE and RMSE are often used as relative measures for comparing forecasts for the same series across different models while the Theil's statistic allows for comparison with the random walk (RW) model and Theil's statistic less than 1 indicates that the model being used is better than the RW model. From Table 9, the dynamic (multi-step-ahead) forecast evaluation results for GARCH (1,1) and EGARCH (1,1) are presented. Results reveal that the EGARCH-type model exhibit better forecast performance than the GARCH model employed as the MAE is lower for all markets except for that of Indonesia at forecast horizons of 1, 3, 6 and 12 weeks respectively. In addition, forecast results show that volatility predictions over shorter term horizons are generally more accurate than over longer term horizons as the MAE are smaller. One possible reason for the EGARCH model outperforming the GARCH model could be due to the exponential specification of the model. The forecast algorithm for the EGARCH-with-skewed-t model is yet to be resolved in the literature. But from the results above, we can infer that models with exponential specification tend to perform better than those without exponential specification in terms of out-of-sample forecasting.

Table 9: **Out-of-Sample Forecast Performance of Selected fitted Models**

Countries		**GARCH (1,1)**				**EGARCH(1,1)**			
	Horizon	1	3	6	12	1	3	6	12
Mexico	RMSE	0.01264	0.01636	0.01715	0.02257	0.01243	0.01605	0.01682	0.02241
	MAE	0.01114	0.01387	0.01391	0.01732	0.01114	0.01364	0.01372	0.01709
	Theil Coeff.	0.81921	0.91027	0.92179	0.88339	0.83019	0.91619	0.92705	0.89296
Indonesia	RMSE	0.00989	0.02841	0.02295	0.01950	0.00986	0.02837	0.02296	0.01952
	MAE	0.00986	0.02432	0.01911	0.01639	0.00986	0.02432	0.01920	0.01644
	Theil Coeff.	0.62501	0.84657	0.80219	0.77148	0.65055	0.86254	0.82193	0.79324
Nigeria	RMSE	0.02285	0.01634	0.02692	0.02371	0.02290	0.01638	0.02693	0.02372
	MAE	0.02285	0.01300	0.02033	0.01935	0.02290	0.01304	0.02035	0.01936
	Theil Coeff.	0.92336	0.86783	0.95575	0.93879	0.92696	0.87103	0.95662	0.93928
Turkey	RMSE	0.04871	0.03758	0.03465	0.02826	0.04854	0.03740	0.03449	0.02815
	MAE	0.04148	0.03035	0.02655	0.02093	0.04147	0.03022	0.02644	0.02087
	Theil Coeff.	0.87580	0.86835	0.87156	0.83041	0.87235	0.86709	0.87190	0.83272
Japan	RMSE	0.01239	0.01575	0.02128	0.02856	0.01211	0.01541	0.02218	0.02845
	MAE	0.00895	0.01336	0.01839	0.02315	0.00857	0.01297	0.01919	0.02294
	Theil Coeff.	0.97927	0.99108	0.99415	0.97799	0.98775	0.99478	0.99694	0.98746
USA	RMSE	0.00405	0.01537	0.01409	0.01313	0.00399	0.01484	0.01398	0.01305
	MAE	0.00399	0.01109	0.01037	0.01037	0.00399	0.01065	0.01025	0.01029
	Theil Coeff.	0.56621	0.92748	0.84712	0.83252	0.63753	0.94625	0.88812	0.87692
Germany	RMSE	0.02313	0.02557	0.02373	0.02486	0.01334	0.02524	0.02364	0.02473
	MAE	0.01953	0.02125	0.01933	0.02033	0.01012	0.02125	0.01918	0.02025
	Theil Coeff.	0.84437	0.90765	0.87145	0.88143	0.92563	0.92925	0.90173	0.90949
France	RMSE	0.00639	0.02249	0.01992	0.01964	0.00569	0.02214	0.01995	0.01962
	MAE	0.00509	0.01681	0.01505	0.01486	0.00417	0.01635	0.01492	0.01479
	Theil Coeff.	0.92368	0.94761	0.90742	0.91045	0.94789	0.97092	0.94876	0.95033

Notes: The table reports the mean absolute error (MAE), root mean squared error (RMSE) and Theil's coefficient statistic at forecast horizons of 1, 3, 6 and 12 weeks respectively. The forecast evaluation statistics presented above are for the conditional mean forecasts. The out-of-sample forecast sample is December, 30th 2013 to March, 31st 2014.

6 Concluding Remarks

Over the years, GARCH models have been used to estimate and forecast volatility of returns, which is important for investment decisions, option pricing and market regulation (see, Zivot, 2009 and Babikir *et al.*, 2012). The aftermath of GFC has led to increased focus on risk management and on GARCH-type models as market estimates of volatilities are increasingly used as a measure of the vulnerability of financial markets, and as aids to policy makers in the design of appropriate policies (Babikir *et al.*, 2012). Against this backdrop, we examined stock market volatility of a group of "newly" EMs and DMs. In an attempt to identify the impact of sudden changes on volatility persistence and on stock markets, we endogenously detect break points where sudden change in returns occur using the ICSS test and then incorporate the variance breaks into the EGARCH(1,1) model. We find that significant variance shifts are associated with GFC, AFC as well as country specific economic and political events ranging from policy changes, debt crises, interest rate cuts to changes in government. Accordingly, we find that when breaks are incorporated into GARCH models, the level of persistence diminishes. Therefore, including information on sudden changes in variance can help improve the accuracy of estimating volatility and on examining the behaviour of stock indices. The paper concludes that EGARCH-with-skewed-t density model exhibits improved diagnostics compared to the standard (a)symmetric GARCH models (with normal or Student's t densities) in the context of skewness, leverage and fat tails.

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Appendix

Table A.1: Unit Root Tests: Zivot and Andrews (1992) and Lee and Strazicich Break Tests

Panel A: Zivot-Andrews Unit Root Test						
	Model A (Crash model)		Model B (Changing growth)		Model C (Mixed model)	
Countries	**t-statistic**	**Break-date**	**t-statistic**	**Break-date**	**t-statistic**	**Break-date**
Mexico	-13.1628^a	2007:07:09	-13.0579^a	1997:02:10	-13.1739^a	1997:08:04
Indonesia	-10.7160^a	2002:10:22	-10.5835^a	2004:11:02	-10.7089^a	2009:03:10
Nigeria	-19.4722^a	1997:04:21	-10.8346^a	1997:09:29	-11.2758^a	2008:03:10
Turkey	-25.8505^a	2000:01:28	-12.7799^a	2001:07:20	-25.9660^a	2000:01:28
Japan	-12.9825^a	2009:03:03	-12.9692^a	2010:12:21	-13.1988^a	2007:07:17
USA	-12.4983^a	2009:03:09	-12.1090^a	2008:10:06	-12.4894^a	2009:03:09
Germany	-12.4831^a	2000:03:13	-12.2389^a	2002:06:03	-12.5260^a	2003:03:17
France	-12.5176^a	2000:09:04	-12.2914^a	1997:02:10	-12.6419^a	2000:03:06
Panel B: Lee and Strazicich (Two-breaks Test)						
Countries	**S(1)**	**Constant**	**Break-date**	**Break-date**	**Test stat**	**T-stat (const)**
Mexico	-1.0004	0.0563	1999:07:19	2007:07:23	-32.2012^a	20.7698^a
Indonesia	-1.0935	-0.0178	1999:04:20	2007:10:23	-14.6887^a	-2.7994^a
Nigeria	-0.9193	-0.0209	1997:03:24	2008:02:04	-25.0647^a	-10.7139^a
Turkey	-0.7769	-0.1276	1999:02:19	2001:03:09	-1.8304^a	-2.3360^a
Japan	-1.0938	0.0324	1998:12:29	2001:09:18	-23.7229^a	14.1591^a
USA	-1.1819	-0.0129	1998:07:13	2001:08:27	-23.8577^a	-8.4791^a
Germany	-1.0539	0.0313	1998:07:20	2003:03:03	-33.9697^a	13.6361^a
France	-1.0904	0.0231	2000:09:04	2007:10:08	-35.2396^a	13.2200^a

Notes: Critical values for the ZA test with breaks in the intercept at 1% and 5% significance levels are -5.3400 and -4.8000 respectively, while for the ZA test with trend, the values at 1% and 5% levels are -4.9300 and -4.4200. For model C with break in both intercept and trend, the values are -5.5700 and -5.0800. Superscripts ^{a},^{b} indicates significance levels at 1% and 5%.

Table A.2: ARCH Tests: F and χ^2 Variants

Test	Mexico	Indonesia	Nigeria	Turkey	Japan	USA	Germany	France
F (1-10)	11.59^a	14.25^a	22.23^a	12.21^a	2.37^a	17.81^a	18.75^a	11.17^a
F(3-10)	6.83^a	12.84^a	6.89^a	9.05^a	2.24^b	9.76^a	11.45^a	9.78^a
χ^2–Variant	105.29^a	122.28^a	183.92^a	110.27^a	23.44^a	152.99^a	160.14^a	101.75^a
McLeod-Li	211.59^a	216.69^a	422.93^a	227.05^a	26.97^a	259.97^a	295.29^a	178.89^a

Notes: Numbers in parentheses stand for number of lags. The ^{a},^{b} indicate significance levels at 1% and 5%. McLeod-Li(10) denotes the test with 10 lags while F-Variant(3-10) denotes the F test on lags 3 through 10. The McLeod-Li test statistic is defined as $S_T^{ML} = T(T+2)\sum_{j=1}^{q}[\tilde{r}_j^2/(T-j)]$, where $\tilde{r}$, is the correlation between $\hat{\varepsilon}_t^2$ and $\hat{\varepsilon}_{t-j}^2$, $j = 1, ..., q$, which is asymptotically equivalent to Engle's (1982) LM test (see, Granger and Teräsvirta, 1993).

Table A.3: ARCH Test on the Residuals

Lags	Mexico	Indonesia	Nigeria	Turkey	Japan	USA	Germany	France
1	49.712^a	44.371^a	82.257^a	37.162^a	3.712	88.392^a	36.147^a	14.630^a
2	29.242^a	24.495^a	101.038^a	38.544^a	2.937	47.725^a	44.740^a	15.852^a
3	29.513^a	34.755^a	67.647^a	28.327^a	7.250^a	42.594^a	45.941^a	14.120^a
4	26.894^a	25.127^a	46.217^a	20.903^a	5.562^a	31.927^a	34.411^a	10.639^a
5	21.957^a	21.681^a	37.370^a	16.156^a	4.480^a	26.562^a	27.538^a	10.221^a
6	18.657^a	19.109^a	28.688^a	14.284^a	3.936^a	22.924^a	27.392^a	14.199^a
7	16.250^a	18.916^a	30.691^a	12.658^a	2.394^a	24.250^a	25.535^a	15.597^a
8	14.208^a	17.090^a	26.644^a	11.985^a	2.971^a	22.040^a	22.384^a	13.871^a
9	12.860^a	15.718^a	23.530^a	10.919^a	2.631^a	19.545^a	20.789^a	12.298^a
10	11.599^a	14.248^a	22.233^a	12.215^a	2.373^a	17.805^a	18.750^a	11.166^a

Note: Superscripts ^{a},^{b} indicate significance levels at 1% and 5%.