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Abstract

We investigate stock markets volatility spillovers in selected emerging and major developed markets using multivariate GARCH (MGARCH) models [namely; DVECH, CCC-MGARCH, CCC-VARMA-(A)MGARCH, VAR-EGARCH, BEKK-(A)MGARCH, DCC-MGARCH (with Gaussian and t distributions) and DCC-with-skew-t density]. The paper analyses the impacts of recent global financial crisis (2007–2009) on stock market volatility and examines their dynamic interactions using several MGARCH model variants. Structural break detection test (the ICSS algorithm) finds significant evidence of breaks in the unconditional variance for all the stock market returns. Having fitted several MGARCH models, we modify the BEKK-(A)MGARCH models by including financial crisis dummies to assess their impact on stock market volatilities, spillovers and interactions. Major findings reveal that correlations among emerging markets are lower compared with correlations among developed markets and tend to increase during financial crises. Consistent with extant literature, own-volatility spillovers are to a large extent higher than cross-volatility spillovers especially for emerging markets. The DCC-with-skew-t density model is found to have better diagnostics compared to all other fitted MGARCH models partly due to its taking into account the skewed feature of the returns. Thus, we recommend that in modelling stock market volatility dynamics, skewness, asymmetry and fat tails (features frequently observed in financial time series) should be taken into account in the modelling process.

Keywords: Stock Markets, Volatility, CCC-MGARCH, ICSS, Asymmetry, Spillover, BEKK-MGARCH, VAR-EGARCH, DCC-with-skew-t, Financial Crises

JEL Classification Codes: **G01; G11; G15**

1 Introduction

The global financial crisis (GFC)(2007–2009) and its impact across financial markets have stimulated considerable interest in the analysis of stock market volatility spillovers (see, Hemche *et al.*, 2016; Coudert *et al.*, 2015; Li and Giles, 2015; Kenourgios and Dimitriou, 2015; Miralles-Marcelo *et al.*, 2013, among others). The financial crisis, initially a US incident, spread to other major stock markets and subsequently emerging markets (EMs) causing huge losses for investors, leading to bankruptcies of many financial institutions and decline in investor confidence with consequent negative impact on the global economy. Investor sell-off and uncertainties in EMs eventually led to a period of high volatility in major stock markets. The ever-increasing globalisation of financial markets and the recent incidence of large stock market fluctuations,

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financial crises and market crashes ranging from the Mexican crisis (1994), the Asian financial crisis (AFC)(1997–98), the Russian debt crisis (1998), the Brazilian currency crisis (1999) to the Greek debt crisis (2010 to date), have rekindled interest in how financial markets within and across countries interact. With EMs' increased important role, better understanding of the nature of spillover effect could be of help to investors and regulators in identifying the nature of interaction between EM and developed markets (DMs) and the implications of volatility spillovers especially during periods of financial crises. Investors in DMs are often interested in whether EMs offer portfolio diversification opportunities and vice versa. Engle (2011) argues that financial market instability, business cycle downturns, rising volatilities and inflation are all events that investors fear and are continuously seeking to hedge against these risks. Recent studies argue that highly integrated financial markets tend to transmit shocks more rapidly with the resulting portfolio shift often affecting interest rate, trade finance, exchange rate and eventually real sector economic activity. Li and Giles (2015) argue that if EMs are only weakly integrated with DMs, external shocks may have limited influence on EMs, while DM investors can benefit by including EM stocks in their portfolio, as diversification would reduce risk. In essence, modelling spillover between markets should help provide a better idea of what asset(s) to include/exclude in the portfolio.

Modelling and forecasting volatility and correlations are now at the centre stage of financial econometrics as accurate estimates of volatility and correlation are required in derivative pricing, portfolio optimisation, risk management and hedging strategies (Sadorsky, 2012). Several models of conditional volatility have been proposed in order to evaluate market risk, asymmetric shocks, leverage effects and value-at-risk (VaR). Even prior to the GFC, studies such as Lin *et al.* (1994), Fleming *et al.* (1998) and Tsutsui (2002) have shown how cross-market hedging and common information sharing could lead to spillover of volatility across markets over time. They often attribute the influence of trade and financial linkages as the key factors influencing the transmission mechanism. Recent events in financial markets such as the August 2015 stock market turbulence in China have shown that emerging financial markets in Asia can become a major source of financial shocks that may be transmitted widely, including to advanced economies (see, Guimar̃aes-Filho and Hong, 2016). The inability of existing models (especially those used in financial markets by practitioners) to fully take into account features of skewness and excess kurtosis has been attributed by scholars to be the cause of the recent GFC, along with over-emphasis on short-term risks rather than long-term risks. Engle (2011) notes that long-term negative skewness increases the downside risk and failure to pay attention to long-term risk is a potential explanation for the GFC. There is an ongoing attempt to incorporate key features of returns such as skewness and excess kurtosis into MGARCH estimation and in the analysis of volatility spillover effects among financial markets (see, Bauwens and Laurent, 2005; He *et al.*, 2008; Engle, 2011 and Massaci, 2014).

For instance, when kurtosis is higher than normal, it implies that there is too much concentration of observations around the mean to be consistent with a normal distribution. De Grauwe (2012) reports that models with this feature tend to underestimate the probability of extremely large asset price changes (i.e. such models underestimate the probability of large bubbles and crashes). He *et al.* (2008) highlight interesting economic theories explaining skewness in the marginal distribution of returns. Relevant to our analysis is Hong and Stein's (2003) model (in their analysis of the differences in opinion, short-sales constraints and market crashes), whereby the flow of information among agents move more slowly when the information received is positive than when it is negative, which make the prices to fall more rapidly (on average) than they increase leading to a return distribution with a skewed density (He *et al.*, 2008). Volatility feedback effect has also been offered as another possible explanation to negative skewness. A large expected future volatility tends to lower stock prices by increasing the required return and when future volatility is perceived to be low, the stock prices increase (He *et al.*, 2008). Thus, the effects of small and large future volatility on prices are not symmetric thereby leading to a negatively skewed returns.

Although the idea that financial markets do influence each other is well known (see, Engle *et al.*, 1990 and Koutmos, 1996), the growing integration of financial markets due to globalisation has led to increased attention on stock market interactions and the mechanisms by which stock return movements are transmitted using several techniques [see, Guimarães-Filho and Hong (2016) and Tsutsui and Hirayama (2013) for their analysis of the interaction between Japanese, Korean and Chinese stock markets using volatility and correlation models; Yang *et al.* (2006) examine emerging market crisis and stock market linkages using vector autoregression (VAR) models while Salisu and Oloko (2015) investigate spillover effects between stock and foreign-exchange (FX) markets in Nigeria using a variant of BEKK-vector autoregressive moving average-asymmetric MGARCH (BEKK-VARMA-AMGARCH) model of McAleer *et al.*, 2009]. In addition, Hassan & Malik (2007) analyse the transmission of volatility among different US sector indices with EMs while studies such as Miralles-Marcelo *et al.* (2013) re-examine volatility relations among Spanish firms using MGARCH models. Earlier, McAleer *et al.* (2009) point out that most MGARCH models are concerned with explaining conditional covariance matrices which are required to determine VaR thresholds used for optimal portfolio and risk management.

Figure 1: Emerging and Developed Stock Markets Weekly Indices (1994–2016)

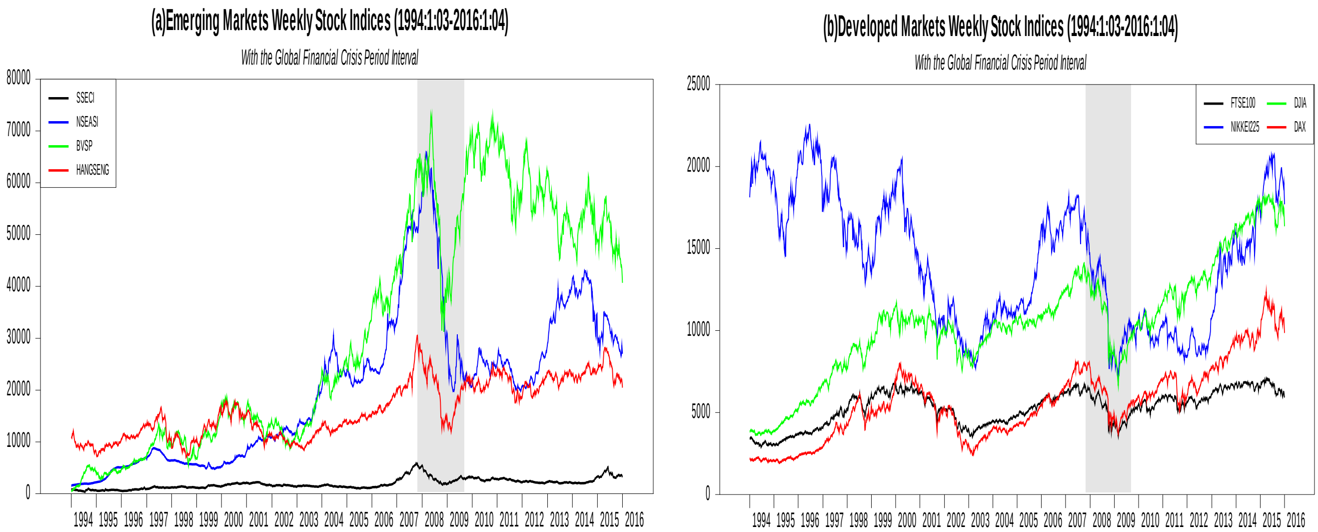


Figure 1 shows that stock markets in both emerging and developed economies all fell and rose significantly and were simultaneously correlated particularly during the GFC (2007–2009) with varying levels of volatility[1]. Until recently, emerging capital markets have been relatively small compared to the sizes of their GDPs. As at mid-2014, EMs have a 39% share of global

[1]Ozer-Imer and Ozkan (2014) note that co-movements became stronger during crashes and crisis periods. Citing Kole (2006) in an attempt to differentiate between a crash and crisis, he states that "while a crash is specific to a single asset, sector or a single market, a crisis can be defined as a period of uncertainty with prolonged effects on many assets and many markets". The term contagion which emanates from the medical field indicating the spread of disease, has been incorporated in the finance literature, defined as a significant increase in correlation between stock returns in different markets/regions during a crisis period, beyond the linkages in fundamentals (see, Kenourgios and Dimitriou, 2015). In addition, the use of copulas to analyse crisis, co-movements and interactions is also been advocated by a small strand of recent literature (see, Kole, 2006; Fengler *et al.*, 2012).

output but 21.6% share of global equity market capitalisation and a 14.4% and 13.9% share of global corporate and sovereign bond markets value respectively (Credit Suisse, 2014). The troughs experienced by all the markets during the 2008–2009 period indicates increased integration among markets during recent financial crisis compared with previous crises periods in our sample. Since early-2016, share prices fell persistently in both EMs and DMs. The reasons advanced for this, include investor concerns due to US interest rate hike, slowdown in Chinese economic growth and plummeting crude oil prices. New studies are focusing on the theoretical basis of share price valuations to explain the share price declines. Falling share prices either indicate that investors have become more pessimistic about future cashflows or that they have raised the applicable discount rate.

To minimise the risk of volatility spillover emanating from China and other EMs, as well as to chieve its other monetary policy objectives, the Bank of Japan (BOJ) recently adopted a negative interest-rate policy. So and Tse (2009) point out that Asian markets are becoming increasingly integrated and that evidence of their co-movements during periods of financial distress is getting stronger. The Chinese stock markets for instance, have undergone significant changes and growth since 1991. The Bovespa (BVSP) index showed trends which could partly be associated with Brazil's financial and currency crises of the early- to mid-1990s. Recently, stock prices in Brazil became highly sensitive to economic data from Asia as China has replaced the USA as its biggest buyer of commodities. A key feature of EMs is that their aggregate equity skew towards resources (such as materials and energy), telecoms and information technology (IT) sectors while for DMs, IT, industrials, technology and healthcare sectors are the most represented (Credit Suisse, 2014). For the European markets, the German DAX-30 index experienced increased volatility even after the GFC largely connected to the EU debt crises that severely affected Greece, Italy and Spain; and raised concerns about the future of the Euro currency.

Several MGARCH models have been proposed and despite their extensive application in the analysis of financial markets and assets in terms of co-movement, contagion, spillover and asymmetric effects, not many studies have actually compared these models empirically. Additionally, the conditional density assumption should be consistent with common stylised facts of asset returns that include conditional hetersocedasticity, skewness and excess kurtosis of which most previous studies did not take into account. This has implications for risk measurement, portfolio allocation and on the propagation of risk across different markets. This paper intends to contribute to the literature in this regard as the methodological frameworks used are relatively new. This study extends the works of Massaci (2014) and others who employs a univariate two-regime threshold model with returns following a distinct skewed Student's t distribution. Accordingly, we will address the following questions: (1) How has correlations in asset returns and volatilities in both EMs and DMs changed over time?(2) Are stock markets more correlated during periods of significant financial crises?(3) Is the DCC-with-skew-t density model superior to all other fitted MGARCH models that do not take into account the often skewed feature of returns?

Recent studies now focus on the impact of shocks on third (skewness) and higher (e.g. kurtosis) moments of a distribution (see, Back, 2014 and Kim *et al.*, 2014). Bauwens and Laurent (2005) propose a flexible method to introduce skewness in multivariate symmetric distributions and apply their procedure to the multivariate Student's t density leading to a multivariate skew-Student's t density. In addition, Massacci (2014) proposes a two-regime threshold model for the conditional distribution of stock returns whereby returns follow a distinct skewed-Student's t distribution within each regime, i.e. the model enables the capturing of time variation in the conditional distribution of returns and its higher order moments. He finds that the model estimates conditional volatility more accurately and produces useful risk assessment as measured by the term structure of VaR. In contrast with the massive literature on univariate GARCH models, not much studies exist on robust estimation of MGARCH models in the presence of large one-off jumps. Laurent *et al.* (2013) propose a multivariate volatility forecasting model, known as the bounded innovation propagation-cDCC (BIP-cDCC) model. The model extends the DCC specification, produces a reasonable out-of-sample covariance forecasts and leads to portfolios with similar return characteristics but lower turnover to the DCC model.

This paper analyses stock market volatility spillovers and investigate the pattern of stock return volatility and the impact of the GFC on stock market interactions by incorporating variance shifts in MGARCH-type model estimations. Further, we seek to contribute to the literature on the impact of financial crises on stock markets by analysing volatility spillovers and cross-market linkages in EMs vis-à-vis DMs in the context of competing distributional assumptions with emphasis on DCC-with-skew-t density models. This can help guide investors and portfolio managers on potential gains from portfolio diversification and on the emerging dynamics of spillover effects in financial markets. Accordingly, insights from the results can provide additional information to policymakers, analysts and investors especially in a period of increasing globalisation of the world economy and stock markets. The rest of the paper is structured as follows: Section 2 reviews related literature while Section 3 outlines MGARCH methodologies and their statistical properties, key distributional assumptions and the iterated cumulative sum of squares (ICSS) algorithm. Section 4 describes the data and discusses results and implications of the fitted MGARCH models while Section 5 concludes. Additional results are presented in the Appendices.

2 Review of Related Literature

The pioneering articles on autoregressive conditional heteroscedasticity (ARCH) by Engle (1982) and Bollerslev (1986) introduce univariate volatility models with subsequent extensions aimed at greater flexibility proposed by Nelson (1991), Glosten *et al.* (1993) and Baillie *et al.* (1996), among others. The "second generation" studies extend the univariate models to multivariate models (MGARCH) starting with the VEC model of Bollerslev *et al.* (1988), diagonal vector conditional heteroscedasticity (DVECH) model and extensions such as Bollerslev's (1990) constant conditional correlation-GARCH (CCC-GARCH), Engle and Kroner's (1995) Baba-Engle-Kraft-Kroner (BEKK)-GARCH, Engle's (2002) dynamic conditional correlation (DCC)-GARCH (DCC-GARCH) and Tse and Tsui's (2002) time-varying CC-GARCH (TVCC-GARCH) models. Others are Ling and McAleer's (2003) VARMA-GARCH, DCC-with-skew-t model proposed by Bauwens and Laurent (2005), McAleer *et al.'s* (2009) VARMA-AGARCH model, BIP-cDCC model proposed by Laurent *et al.* (2013), etc. It is now common to examine large number of assets, e.g. bonds with different maturities, multiple currencies, diverse equities, etc. This influenced the development of several MGARCH model variants.

Influential studies on volatility interactions and spillovers include; Ling and McAleer (2003), Cappiello *et al.* (2006), Bauwens *et al.* (2006, 2013 and references therein), Silvennoinen and Teräsvirta (2009), Nakatani and Teräsvirta (2009), Conrad and Karanasos (2010) and Laurent *et al.* (2012). Several empirical evidences were provided in the literature suggesting that financial markets do influence each other. During financial crises, currency volatility also becomes an issue of concern particularly to monetary authorities and international investors. In a bid to diversify, investors might pick an outperforming stock in another market, only to see their gains evaporate due to excessive exchange-rate (FX) movements in another market. However, Bae *et al.* (2003) note that "there does not seem to be strong evidence that stock returns in one country are more highly correlated with returns in other countries during crisis period once one takes into account the fact that correlation estimates are likely biased".

Baumöhl and Lyocsa (2014) examine within the dynamic conditional correlation (DCC) context, the relationship between time-varying correlations and conditional volatility among 32 emerging and frontier markets and the MSCI stock index from 2000 to late-2012. They find that asymmetry is not a common phenomenon in EMs and that the relations between volatility and correlations is positive and significant in most countries. Kenourgios and Dimitriou (2015) investigate spillover effects during the GFC among 10 sectors in 6 developed and emerging regions. They examine different channels of financial contagion using DCC from the multivariate fractionally integrated asymmetric power-ARCH (FIAP-ARCH) model. They find that the GFC can be characterised by spillover effects across stock markets and (non) financial sectors and that developed Pacific region and sectors like consumer goods, healthcare and technology seems to be less affected by the GFC while the most vulnerable sectors were in emerging Asian and EU regions. Ozer-Imer and Ozkan (2014) investigate the impact of recent GFC on the co-movement of 16 currencies using Engle's (2002) DCC approach. They find that volatilities increase atleast two-folds with the outbreak of crisis and that an inverse relationship between volatility and duration of the crisis exists.

Although univariate GARCH models have been successful in capturing symmetric conditional volatility features in financial returns, they assume independence between conditional volatilities across markets and assets. That is, they do not examine the existence of cross-asset, cross-market and cross-country effects nor test for non-zero conditional correlations useful in optimal portfolio management. This paper empirically analyse and compare several MGARCH specifications using stock returns data in order to examine spillover and asymmetric effects across both EMs & DMs and interactions in conditional volatilities in the context of the GFC. Koutmos (1996) investigates the dynamic interdependence of major European stock markets with focus on first and second moment stock market interactions, by extending Nelson's (1991) EGARCH specification to a multivariate model. We will revisit this specification (VAR-EGARCH) in our analysis of spillover effects and compare with similar models to analyse interactions in major stock markets.

Time-varying correlations are often estimated with MGARCH models that are linear in squares and cross products of the series (see, Bollerslev, 1990; Kroner and Ng, 1998; Cappiello *et al.*, 2006, etc.). Engle (2002) proposes the DCC model which is nonlinear but can be fitted with univariate or two-step based methods on the likelihood function (with a series of univariate GARCH and correlation estimates). He states that the DCC model "can be viewed as a generalisation of the Bollerslev's (1990) CCC estimator". He finds that the bivariate DCC model provides a very good approximation to a variety of time-varying correlation processes. Engle and Shephard (2001) develop the theoretical and empirical properties of a DCC-MGARCH model. They simplify the problem of multivariate conditional variance estimation by fitting univariate GARCH models for each asset before using the transformed residuals arising from that, to estimate a conditional correlation estimator. Similarly, Cappiello *et al.* (2006) propose the asymmetric generalised-DCC (AG-DCC) model which extends previous specifications by allowing for series-specific news impact/smoothing parameters and conditional asymmetries in correlation dynamics among different asset classes. In addition, they investigate the presence of asymmetric responses in conditional variances and correlations to negative returns.

Alper and Yilmaz (2004) examine stock market volatility spillover from EMs and financial centres to the Turkish stock market in the period 1992 to 2001 using GARCH models. They find evidence of volatility spillover from the financial centers during the AFC to the Istanbul stock exchange. Bauwens *et al.* (2006) and Allen *et al.* (2011) point out that the most appropriate use of MGARCH models is in modelling the volatility of certain markets in relation to the co-volatility of other markets. That is, these models should be used to determine if the volatility of one market leads to the volatility of other markets (known as "spillover effects"). Bauwens *et al.* (2006) claim that these models are also efficient in determining whether volatility is transmitted between financial markets through the conditional variance (directly) or conditional covariances (indirectly), whether shocks to one market increase the volatility of another market and the magnitude of that increase, and whether negative information has the same impact as positive information of equal magnitude (Allen *et al.*, 2011).

Similarly, Berben and Jansen (2005) employ TVCC-GARCH model to examine whether stock markets have become more integrated in the sense that correlations between volatilities in these markets have become stronger over time. Bauwens *et al.* (2013) propose a new multiplicative multivariate DCC (mDCC) model that allows for both smooth changes in the unconditional volatilities and correlations and for conditional volatility and correlations clustering around the smoothly changing level. The volatility interactions literature is not limited to only stock markets but extends to the FX market (see, West and Cho, 2005 and Rapach and Strauss, 2008), equity and bond markets (see, Cappiello *et al.*, 2006), energy markets (see, Bauwens *et al.*, 2013), oil and stock markets (see, Sadorsky, 2012; Salisu and Oloko, 2015); stock and FX markets (see, Salisu and Oloko, 2015), and several others. Sadorsky (2012) employs MGARCH models (BEKK, DVECH, CCC and DCC specifications) to model conditional correlations and to analyse the volatility spillovers between oil price and the stock prices of clean energy and technology companies. By comparing and contrasting the models, Sadorsky finds that the DCC model best fits the data with results showing that the stock prices of clean energy companies correlate more strongly with technology stock prices than with oil prices.

An established stylised fact of financial returns is that they exhibit fat tails (kurtosis larger than 3), asymmetry and skewness. To account for these features, new studies consider more flexible distributions than both normal and Student's-t density such as: multivariate skew-t and the generalised hyperbolic (GH) skew-Student's-t densities. Doan (2013) observes that most MGARCH models are fitted using either multivariate normal or t densities for the residuals with both belonging to a class of elliptically symmetrical densities. This is because the Student's-t cannot have fatter tails in some directions and is not permitted to be skewed. In Bauwens and Laurent (2005) the skewed (univariate) distribution is constructed from a symmetrical distribution. They demonstrate this by converting symmetrical densities to skewed ones which can be applied to any well behaved symmetrical univariate density to create a skewed multivariate one (see, Bauwens and Laurent, 2005 and Doan, 2013). Combined with MGARCH model, they find that this family of distributions is more useful than its symmetric cousin for modelling stock returns and for forecasting the VaR of portfolios. In this paper we augment Engle's (2002) DCC model with multivariate skew-t density in order to give additional flexibility to the fitted DCC model. Recent studies have emphasised the importance of modelling the skewness and kurtosis properties of financial returns in asset pricing models (see, Aas and Haff, 2006; Engle, 2011 and Massacci, 2014, among others). Bauwens and Laurent (2005) stress that "although GARCH model generates excess kurtosis when combined with a Gaussian conditional density, it does not fully account for the excess kurtosis present in most return series".

Narayan *et al.* (2014) examine the patterns and causes of stock market integration of selected Asian EMs against the US, China, Australia and India using DCC model. Utilising daily, weekly and monthly data from 2001 to 2012, they find that opportunities in cross border investment vary by frequency and that correlations were strongest during the GFC period. In addition, they find that while the GFC may have amplified the integration process of stock markets, other factors such as globalisation and economic integration, trade linkages and domestic stock market characteristics may also have contributed to the increased correlations. Furthermore, they note that financial liberalisation, foreign investment flows as well as the presence of country funds and/or cross-listed securities also integrates national markets with global capital markets (Narayan *et al.*, 2014). Despite the attractive features of the original DCC which has proven to be reliable in empirical studies, Hafner and Reznikova (2012) propose a more complex version of the DCC model mainly to address some of its limitations as Engle's (2002) DCC model does not perform well when large number of assets are involved. Fengler *et al.* (2012) examine the dynamic Copula based approach to recovering the index implied volatility skew for the case of the German DAX-30 stock index. They show that moderate tail dependence coupled with asymmetric correlation response to negative news is essential in explaining the index implied volatility skew while the standard DCC models with zero tail dependence fail to generate sufficiently steep implied volatility skew. The multivariate models they employ belong to the class of Copula asymmetric-DCC (C-DCC) models.

Li and Giles (2015) examine volatility spillovers between developed (USA and Japan) and 6 Asian developing economies (China, India, Malaysia, Indonesia, the Philippines, and Thailand). Using an asymmetric BEKK-MGARCH model earlier proposed by Engle and Kroner (1995) and later extended by Kroner and Ng (1998), they find significant unidirectional shock and volatility spillovers from the US market to both Japanese and the Asian EMs. They also find that volatility spillovers between the US and the Asian markets are stronger and bidirectional during the AFC. Coudert *et al.* (2015) examine financial integration (internationalisation versus regionalisation) in EMs using a rolling window OLS regression (to evaluate to what extent shocks in regional and DMs are transmitted to EMs) and a trivariate BEKK-MGARCH model (to assess the dynamics of integration and regionalisation in EMs). They find that the pattern of financial shock to transmission vary substantially across economies and over time. Hemche *et al.* (2016) investigate the contagion hypothesis for 10 developed and mostly second-level EMs with respect to the US market in the context of the subprime crisis (2007), GFC (2008–2009) and the great recession (2009) using a DCC-MGARCH model. They find using Forbes and Rigobon's (2002) contagion test, a significantly higher correlation between markets during the crises. They note that their analysis provide insights into the investment and diversification opportunities still possible in some EMs. In terms of diversification strategies, industry and country diversification have been recommended in the literature. Recent research shows that focus on industries rather than countries have gained more attention. Zhou and Nicholson (2015) recommend mixed-asset portfolio diversification. However, investors should consider both industry and country diversification in building their portfolios and in hedging against risk.

Engle (2011) develops a test for long-term skewness in order to examine whether standard volatility models are capable of modelling this characteristic of the data and the risk it generates. Aas and Haff (2006) argue in favour of a special case of the generalised hyperbolic (GH) skew Student's t distribution in modelling financial data as it has the key property that one tail has polynomial and the other exponential behaviour. They demonstrate the superiority of this class of distribution compared with some of its competitors through VaR and expected shortfall calculations. However, the GH skew-Student's t distribution is not well known and its special tail behaviour has not yet been addressed. Guimarães-Filho and Hong (2016) examine the connectedness of Asian equity markets within the region vis-à-vis other major global markets using time-varying connectedness measures (based on dynamic variance decompositions from a VAR applied to asset returns and volatilities). They address a number of questions ranging from: whether markets become more connected during crises period, which markets are major sources and recipients of shocks, to how connectedness in asset returns and volatilities changed over time. Finally, they investigate the connectedness between China's equity markets and other major equity markets since August, 2015 in order to highlight the growing importance of EMs particularly China as a new source of shocks. The next section describes the econometric methodologies to be employed in the study.

3 Econometric Methodologies

In this section, we describe the relevant models to be used in our analysis and their main econometric properties as well as the overall estimation strategy. To determine the stationarity of the returns data to be used, we conduct unit root tests, with and without structural breaks. Furthermore, we employ Inclan and Tiao's variance breaks detection test to detect the number and position of break points in variance of the returns data. We then estimate several variants of MGARCH models, namely; (a) DVECH, (b) CCC-MGARCH, (c) CCC-VARMA-(A)MGARCH, (d) VAR-EGARCH, (e) BEKK-(A)MGARCH, (f) DCC-MGARCH (with Gaussian and t distributions) and (g) DCC-with-skew-t density. In addition, we modify the BEKK-(A)MGARCH models by including financial crisis dummies to assess their impact on stock market volatilities and interactions. We use weekly stock market returns data from 1994 to 2016 for market indices in Nigeria, Hong Kong (China) and Brazil (EMs) and Japan, USA, and UK (DMs). The respective models are specified below.

3.1 Unit Root Tests With and Without Structural Breaks

3.1.1 The Augmented Dickey-Fuller Test (Without Structural Breaks)

The augmented Dickey-Fuller (ADF) test is based on eqn.(1) below

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

where Δy_t is the first difference of y_t series and ε_t is the residual with $\Delta y_{t-1} = y_{t-1} - y_{t-2}, \Delta y_{t-2} = y_{t-2} - y_{t-3}$, and so on. If the series is trend-stationary, α will be negative thereby forcing the series to revert to trend from any deviation (Enders and Doan, 2014). The Δy_{t-i} is added to eliminate serial correlation in ε_t. Eqn.(1) tests the null (unit root) hypothesis against the alternative (stationary) hypothesis.

3.1.2 Zivot and Andrews (ZA) Unit Root Test (With Structural Breaks)

The Zivot and Andrews (1992) test allows for a single break (at an unknown date) in the intercept, trend and/or in both intercept and trend. ZA 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 $DU_t = 1$ 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 state 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 (the point where the unit root t-test statistics is minimised).

3.2 Multivariate Generalised-ARCH (MGARCH) Models

Suppose $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, ..., \varepsilon_{mt})'$ such that $\mathbf{E}\boldsymbol{\varepsilon}_t = \mathbf{0}$ and $\mathbf{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'|\mathcal{F}_{t-1}) = \mathbf{H}_t$, where $\mathbf{H}_t$ is positive definite and $\boldsymbol{\varepsilon}_t = \mathbf{H}_t^{0.5}\mathbf{z}_t$ with $\mathbf{z}_t \sim i.i.d.(\mathbf{0}, \mathbf{I}_m)$. The $\mathcal{F}_{t-1}$ contains past market information up to time $t-1$. The conditional variance equation in the spirit of Bollerslev *et al.* (1988) is of the form defined in eqn.(3) as

$$vech(\mathbf{H}_t) = \mathbf{C} + \sum_{k=1}^{q} \mathbf{A}_k vech(\boldsymbol{\varepsilon}_{t-k}\boldsymbol{\varepsilon}_{t-k}') + \sum_{k=1}^{p} \mathbf{B}_k vech(\mathbf{H}_{t-k}), \tag{3}$$

where *vech* denotes the half-vectorisation operator which stacks the columns of a square matrix from the diagonal downwards in a vector. The $\mathbf{A}_k = [\alpha_{kij}]$ and $\mathbf{B}_k = [\beta_{kij}]$ are coefficient matrices with $m(m+1)/2$ rows and columns, and $\mathbf{C}$ is an $[m(m+1)/2] \times 1$ intercept vector with positive elements. The DVECH uses only the diagonal elements of $\mathbf{A}_k$ and $\mathbf{B}_k$, and sets all values of $\alpha_{ij} = \beta_{ij} = 0$, for $i \neq j$. In Bollerslev's (1990) model, $\mathbf{H}_t = \mathbf{D}_t\mathbf{R}\mathbf{D}_t$, where $\mathbf{D}_t$ (is the diagonal matrix) and $\mathbf{R}$ (the correlation matrix) contains the conditional correlations independent of t. Due to limitations of the CCC model which presumes that the conditional variances are independent across returns, Ling and McAleer (2003) propose the VARMA-MGARCH model (the CCC-MGARCH is a special case). The model assumes that shocks (positive or negative), have identical impacts on conditional variance (i.e. it neglects asymmetric behaviour). To address this shortcoming, McAleer *et al.* (2009) propose a VARMA-AGARCH specification given in eqn.(4) below

$$\mathbf{H}_t = \mathbf{C}^* + (\mathbf{A}^*)\boldsymbol{\varepsilon}_{t-1}^2 + \mathbf{D}^* I_{t-1}\boldsymbol{\varepsilon}_{t-1}^2 + (\mathbf{B}^*)\mathbf{H}_{t-1}, \tag{4}$$

with $\mathbf{H}_t = (h_{1t}, ..., h_{mt})'$, where $\mathbf{C}^*, \mathbf{A}^*$ and $\mathbf{B}^*$ are $m \times m$ matrices of constants, ARCH and GARCH terms respectively. The $\mathbf{D}^*$ is an $m \times m$ matrix. The I_t =diag$(I_{1t}, ..., I_{mt})$ captures the asymmetric effect such that $I_t = 0$ if $\varepsilon_{it} > 0$ and $I_t = 1$ if otherwise. The I_t is an indicator function. The VARMA-AMGARCH specification reduces to VARMA-MGARCH when $\mathbf{D}^* = 0$ (see, Allen *et al.*, 2011). For the BEKK-MGARCH model, its main advantage is that its variance-covariance matrices are always positive definite. The BEKK(1,1) model is given by

$$\mathbf{H}_t = (\mathbf{C}^*)'\mathbf{C}^* + (\mathbf{A}^*)'(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}')\mathbf{A}^* + (\mathbf{B}^*)'\mathbf{H}_{t-1}\mathbf{B}^*, \tag{5}$$

where $\mathbf{C}^* = (\mathbf{c}_1', ..., \mathbf{c}_m')'$ is an $m \times m$ triangular matrix, $\mathbf{A}_{jk}^* = [\alpha_{jk,il}^*]$ and $\mathbf{B}_{jk}^* = [\beta_{jk,il}^*]$ are $m \times m$ coefficient matrices. The $(\mathbf{C}^*)'\mathbf{C}^*$ is positive definite when $\mathbf{C}^*$ is of full rank (Teräsvirta *et al.*, 2010). The elements of $\mathbf{A}^*$ capture the effects of shocks on volatility while the elements of $\mathbf{B}^*$ capture the effects of past conditional variances measuring the diagonal parameters of the effects of past own shocks and past volatility in both cases (see, Miralles-Marcelo *et al.*, 2013). Eqn.(6) present the decomposed version of eqn.(5) element by element. For the conditional variance of eqn.(5), the total number of elements is 24.

$$\mathbf{H}_t = \begin{pmatrix} c_{1,1} & & \\ c_{2,1} & c_{2,2} & \\ c_{3,1} & c_{3,2} & c_{3,3} \end{pmatrix} \begin{pmatrix} c_{1,1} & c_{2,1} & c_{3,1} \\ & c_{2,2} & c_{2,3} \\ & & c_{3,3} \end{pmatrix} + \begin{pmatrix} \alpha_{1,1}^* & \alpha_{1,2}^* & \alpha_{1,3}^* \\ \alpha_{2,1}^* & \alpha_{2,2}^* & \alpha_{2,3}^* \\ \alpha_{3,1}^* & \alpha_{3,2}^* & \alpha_{3,3}^* \end{pmatrix} \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}' \begin{pmatrix} \alpha_{1,1}^* & \alpha_{2,1}^* & \alpha_{3,1}^* \\ \alpha_{1,2}^* & \alpha_{2,2}^* & \alpha_{3,2}^* \\ \alpha_{1,3}^* & \alpha_{2,3}^* & \alpha_{3,3}^* \end{pmatrix} +$$

$$\begin{pmatrix} \beta_{1,1}^* & \beta_{1,2}^* & \beta_{1,3}^{*2} \\ \beta_{2,1}^* & \beta_{2,2}^* & \beta_{2,3}^* \\ \beta_{3,1}^* & \beta_{3,2}^* & \beta_{3,3}^* \end{pmatrix} \mathbf{H}_{t-1} \begin{pmatrix} \beta_{1,1}^* & \beta_{2,1}^* & \beta_{3,1}^{*2} \\ \beta_{1,2}^* & \beta_{2,2}^* & \beta_{3,2}^* \\ \beta_{1,3}^* & \beta_{2,3}^* & \beta_{3,3}^* \end{pmatrix}, \tag{6}$$

where

$$\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1} = \begin{pmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} & \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}\varepsilon_{1,t-1} & \varepsilon_{3,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{3,t-1} \end{pmatrix}, \mathbf{H}_t = \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{pmatrix}.$$

Considering the trivariate case, the elements of $\mathbf{H}_t$ in eqn. (5) are

$$\begin{cases} h_{11,t} = c^2_{1,1} + \alpha^{*2}_{11}\varepsilon^2_{1,t-1} + \alpha^{*2}_{21}\varepsilon^2_{2,t-1} + \alpha^{*2}_{31}\varepsilon^2_{3,t-1} + 2\alpha^*_{11}\alpha^*_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2\alpha^*_{11}\alpha^*_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + \\ 2\alpha^*_{31}\alpha^*_{21}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + \beta^{*2}_{11}h_{1,t-1} + \beta^{*2}_{21}h_{2,t-1} + \beta^{*2}_{31}h_{3,t-1} + 2\beta^*_{11}\beta^*_{21}h_{12,t-1} + 2\beta^*_{11}\beta^*_{31}h_{13,t-1} \\ +2\beta^*_{31}\beta^*_{21}h_{23,t-1}, \\ h_{22,t} = c^2_{2,1} + c^2_{2,2} + \alpha^{*2}_{12}\varepsilon^2_{1,t-1} + \alpha^{*2}_{22}\varepsilon^2_{2,t-1} + \alpha^{*2}_{32}\varepsilon^2_{3,t-1} + 2\alpha^*_{22}\alpha^*_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2\alpha^*_{32}\alpha^*_{12}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + \\ 2\alpha^*_{32}\alpha^*_{22}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + \beta^{*2}_{11}h_{1,t-1} + \beta^{*2}_{22}h_{2,t-1} + \beta^{*2}_{32}h_{3,t-1} + 2\beta^*_{22}\beta^*_{12}h_{12,t-1} + 2\beta^*_{32}\beta^*_{12}h_{13,t-1} \\ +2\beta^*_{32}\beta^*_{22}h_{23,t-1}, \\ h_{33,t} = c^2_{3,1} + c^2_{3,2} + c^2_{3,3} + \alpha^{*2}_{13}\varepsilon^2_{1,t-1} + \alpha^{*2}_{23}\varepsilon^2_{2,t-1} + \alpha^{*2}_{33}\varepsilon^2_{3,t-1} + 2\alpha^*_{23}\alpha^*_{13}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2\alpha^*_{33}\alpha^*_{13}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + \\ 2\alpha^*_{33}\alpha^*_{23}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + \beta^{*2}_{13}h_{1,t-1} + \beta^{*2}_{23}h_{2,t-1} + \beta^{*2}_{33}h_{3,t-1} + 2\beta^*_{23}\beta^*_{13}h_{12,t-1} + 2\beta^*_{33}\beta^*_{13}h_{13,t-1} \\ +2\beta^*_{33}\beta^*_{23}h_{23,t-1}. \end{cases} \tag{7}$$

We consider and estimate eqn.(8) which is a BEKK-AMGARCH (with asymmetry) model proposed by Kroner and Ng (1998) in order to capture the asymmetric effects/property of the time-varying variance-covariance matrix. This is expressed as

$$\mathbf{H}_t = (\mathbf{C}^*)'\mathbf{C}^* + (\mathbf{A}^*)'(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1})\mathbf{A}^* + (\mathbf{B}^*)'\mathbf{H}_{t-1}\mathbf{B}^* + (\boldsymbol{\gamma}^*)'\mathbf{G}_{t-1}\mathbf{G}'_{t-1}\boldsymbol{\gamma}^*, \tag{8}$$

which adds the $m \times m$ matrix $\boldsymbol{\gamma}^*$. Asymmetry is a common feature in stock market return data due to the leverage effect phenomenon of equity markets (Teräsvirta *et al.*, 2010). Koutmos (1996) proposes a multivariate CCC-EGARCH model on a VAR equation. The EGARCH specification takes the specialised form in eqns.(9) and (10) expressed as

$$\log h_{it} = c_i + g_i \log h_{i,t-1} + \sum_j \alpha_{ij} z_{j,t-1}, \tag{9}$$

$$z_{jt} = \left(\frac{|\varepsilon_{jt}|}{\sqrt{h_{jt}}} - \sqrt{\frac{2}{\pi}} \right) - d_j \frac{\varepsilon_{jt}}{\sqrt{h_{jt}}}, \tag{10}$$

where c_i, g_i, α, and d_j are variance intercepts in EGARCH, lagged variance coefficients, lagged z term and the asymmetry coefficients respectively. The conditional variance of the return in each market, given by eqn.(9) is a logarithmic function of past own and cross-market standardised innovations. The functional form of z_{jt} is given in eqn.(10) which permits standardised own and cross-market innovations to influence the conditional variance in each market asymmetrically. If α_{ij} is positive, the impact of $z_{j,t-1}$ on $\log h_{it}$ will be positive (negative) if the magnitude of $z_{j,t-1}$ is greater (smaller) than its expected value $(2/\pi)^{0.5}$. Volatility spillovers across markets are measured by α_{ij}. The persistence of volatility implied by eqn.(9) is measured by g_i and the unconditional variance is finite if $g_i < 1$ (see, Nelson, 1991 and Koutmos, 1996). If $\sum_j \alpha_{ij} z_{j,t-1}$ were replaced by $\alpha_{ii} z_{i,t-1}$ it becomes a standard CCC-Asymmetric-EGARCH model. The Koutmos model allows for a "spillover" effect from lagged ε to the variance of i. For the correlations, we assume that the correlations evolve dynamically. We employ Engle's (2002) DCC model. The model can be represented by eqn.(11) below

$$\begin{cases} \mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t, \\ \mathbf{D}_t = \mathrm{diag}(h^{0.5}_{11,t}, ..., h^{0.5}_{kk,t}), \\ \mathbf{Q}_t = (1-\alpha-\beta)\mathbf{R}_t + \alpha(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}) + \beta\mathbf{Q}_{t-1}, \\ \mathbf{R}_t = (\mathrm{diag}\mathbf{Q}_t)^{-0.5}\mathbf{Q}_t(\mathrm{diag}\mathbf{Q}_t)^{-0.5}, \end{cases} \tag{11}$$

where $\mathbf{H}_t$ is the conditional variance matrix and $h_{ii,t}$ is a univariate GARCH equation. The $\mathbf{Q}_t$ is the covariance matrix with typical elements $q_{ij,t}$ as a weighted average of a positive definite and a positive semidefinite matrix. The $\mathbf{R}_t$ is the $m \times m$ unconditional correlation matrix of ε_t while α and β are positive scalar parameters satisfying $\alpha+\beta < 1$ (Bauwens and Laurent, 2005). To further examine time-varying nature of the relations we estimate a new class of MGARCH model with multivariate skew-t densities that allows for skewness in multivariate symmetric distributions. The standardised skew-Student's t density as defined by Bauwens and Laurent (2005) is given by

$$f(\boldsymbol{\varepsilon}|\boldsymbol{\xi},\nu) = \left(\frac{2}{\sqrt{\pi}}\right)^k \left(\Pi_{i=1}^k \frac{\xi_i s_i}{1+\xi_i^2}\right) \frac{\Gamma((\nu+k)/2)}{\Gamma(\nu/2)(\nu-2)^{k/2}} \left(1+\frac{\boldsymbol{\varepsilon}^{*\prime}\boldsymbol{\varepsilon}^*}{\nu-2}\right)^{-(k+\nu)/2}, \tag{12}$$

where $\boldsymbol{\varepsilon}^* = (\varepsilon_1^*, ..., \varepsilon_k^*)'$, $\varepsilon_i^* = (s_i\varepsilon_i+m_i)\xi_i^{I_i}$, $m_i = \frac{\Gamma((\nu-1)/2)\sqrt{\nu-2}}{\sqrt{\pi}\Gamma(\nu/2)}\left(\xi_i-\frac{1}{\xi_i}\right)$ and $s_i^2 = \left(\xi_i^2+\frac{1}{\xi_i^2}-1\right)-m_i^2$. Furthermore, $I_i = -1$ if $\varepsilon_i \geq -\frac{m_i}{s_i}$ and $I_i = 1$ if $\varepsilon_i < -\frac{m_i}{s_i}$, where m and s denote the mean and standard deviation respectively. The m_i and s_i^2 are functions of $\boldsymbol{\xi}$ and ν. The $\boldsymbol{\xi}$ is the vector of asymmetry parameters. Eqn.(12) allows for a heavier tail behaviour than is accommodated by a multivariate skew normal distribution and yields a standardised symmetric multivariate Student's t density if $\xi_i = 1$, for $i = 1, ..., k$. Bauwens and Laurent (2005) argue that using a more appropriate distribution may lead to improved empirical modelling and financial decision making. The main drawback of Gaussian or Student's-t distributions is that their density is symmetric whereas the distribution of financial returns is mostly skewed. Other multivariate asymmetric densities include the multivariate skew-normal density of Azzalini and Dalla Valle (1996) and the generalised hyperbolic (GH) distributions used in Barndoff-Nielsen and Shephard (2001).

3.3 Inclan and Tiao's (IT) Variance Breaks Detection Test

The Inclan and Tiao's (1994) iterated cumulative sum of squares (ICSS) algorithm endogenously detects number and position of break points in variance of series. 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. Inclan 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 as

$$IT = \sup_k |(T/2)^{0.5} D_k|, \tag{13}$$

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, 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 such as GARCH process (see, de Pooter and van Dijk, 2004). The empirical findings are reported in the next section.

4 Data, Results and Discussion

4.1 Data, Descriptive and Market Sensitivity Statistics

We use weekly stock market returns data from January, 1994 to January, 2016 for the Nigerian stock exchange All-share index (NSEASI)(Nigeria), the Nikkei-225 (Japan), Dow Jones Industrial Average (DJIA)(USA), Shanghai stock exchange composite index (SSECI)(China), DAX-30 (Germany), Financial Times stock exchange (FTSE-100)(UK), Bovespa (BVSP)(Brazil), and Hang-Seng (Hong Kong) indices. We compute the continuously compounded return due to its advantages and attractive statistical properties such as stationarity and ergodicity (see, Campbell *et al.*, 1997 and Tsay, 2005). Theoretically, for equally spaced values of an asset price, the log-return process satisfy conditions that include mean zero, constant variance, serially uncorrelated/i.i.d. and jointly normal. The weekly percentage returns are calculated as $r_t = 100 \times (\ln P_t - \ln P_{t-1})$ for $t = 1, 2, ..., 1149$; where r_t is index return, P_t is the stock index value at time t and P_{t-1} is the stock index value at time $t-1$. Each market's return were calculated in the local currency. The sample period coincides with major economic and financial episodes ranging from the AFC, the dot-com bubble in early-2000s, the September 11th incident in 2001 to the GFC (2007–2009). We utilise weekly returns due to data availability, to avoid the nonsynchronous trading and noisy events problems of using daily data (as the trading days in some countries may coincide with public holidays in others) and to avoid time zone differences. However, the use of weekly data may hide interactions lasting for only a few days.

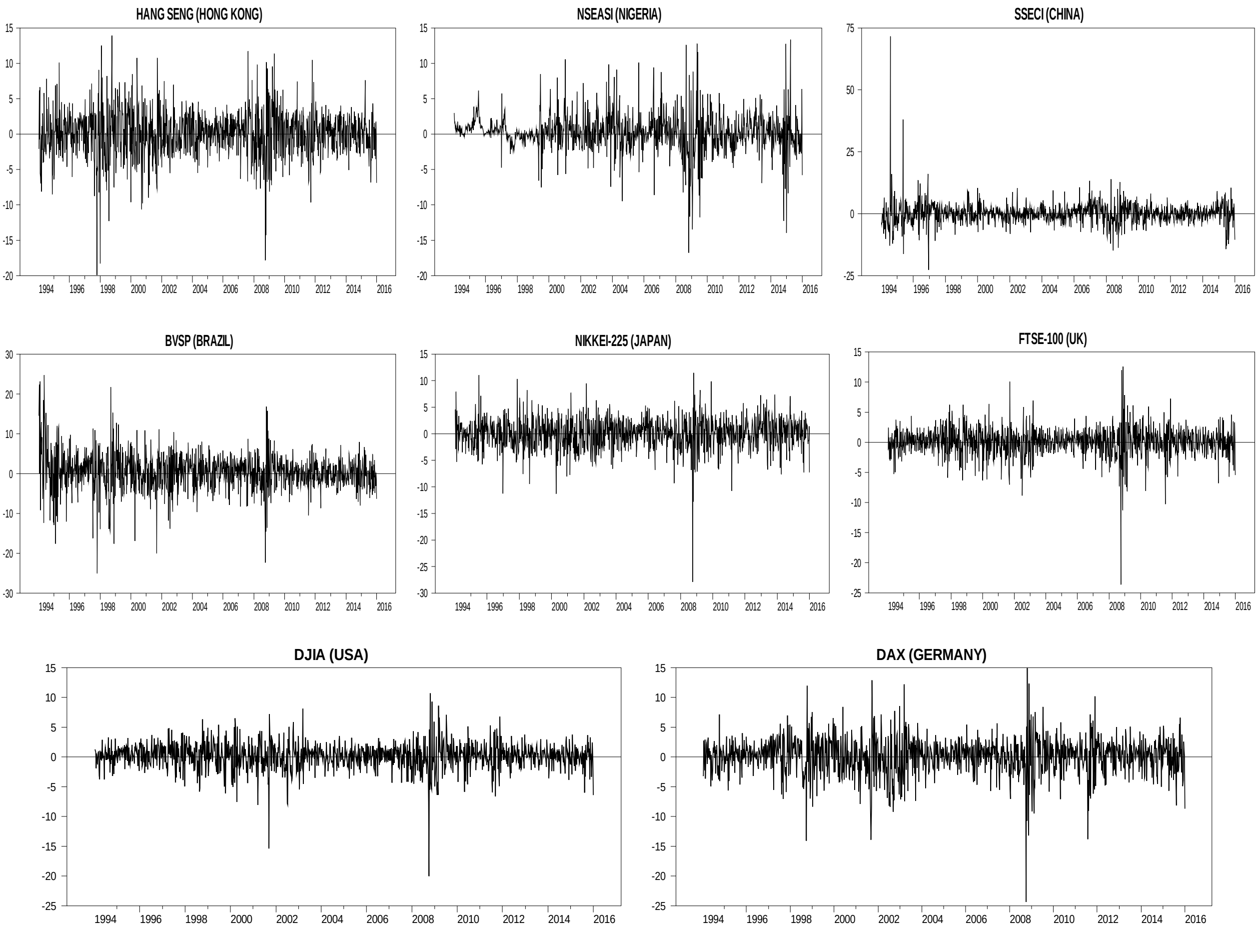
Table 1: Summary Statistics for Weekly Stock Market Returns (1994–2016)

Indices	NSEASI	BVSP	SSECI	Hang-Seng	Nikkei	FTSE	DJIA	DAX
Mean	0.249	0.387	0.112	0.054	-0.002	0.047	0.127	0.130
Median	0.208	0.502	0.033	0.215	0.159	0.209	0.291	0.469
Maximum	13.356	24.772	71.565	13.917	11.449	12.583	10.698	14.942
Minimum	-16.764	-25.059	-22.629	-19.922	-27.884	-23.632	-20.029	-24.347
Std. Dev.	2.751	4.821	4.516	3.403	3.024	2.399	2.337	3.220
Skewness	-0.155*	-0.017	3.802	-0.372**	-0.833**	-0.957**	-0.880**	-0.630**
Kurtosis	8.767**	6.774	62.146	6.092**	9.861**	13.304**	10.255**	7.666**
C.V.	11.048	12.457	40.321	63.019	-1512	51.043	18.402	24.769
Jarque-Bera	1612.22	689.06	170100	489.48	2407.85**	5303.68	2691.97	1128.82
Probability	(0.00)**	(0.00)**	(0.00)**	(0.00)**	(0.00)**	(0.00)**	(0.00)**	(0.00)**
ARCH-LM(5)	29.39**	30.91**	1.310	10.85**	9.89**	15.63**	18.71**	29.22**
ARCH-LM(10)	21.67**	16.69**	0.78	7.94**	5.53**	15.82**	11.08**	20.00**
McLeod-Li (10)	408.29**	412.95**	9.11	144.58**	69.98**	205.57**	150.87**	315.12**
Modified L-B(10)	30.60**	17.75	2.71	6.21	5.14	15.07	12.60	9.59
Modified L-B(20)	40.82**	33.11	9.41	16.64	12.27	15.07	24.02	14.22
Modified $Q^2(10)$	91.52**	119.35**	20.29*	65.76**	14.38	34.20**	40.79**	71.37**
Modified $Q^2(20)$	132.29**	173.75**	30.34	129.04**	20.85	57.27**	76.88**	114.16**
Observations	1149	1149	1149	1149	1149	1149	1149	1149

Note: Std. Dev., C.V., ARCH-LM and modified L-B represent the standard deviation, coefficient of variation, ARCH-Lagrange multiplier test and modified Ljung-Box (LB) (West-Cho modified Q test) respectively. The modified LB test is robust to heteroscedasticity. Superscripts **,* indicate significance at 1% and 5% levels respectively.

Table 1 present summary statistics of the stock market returns, which partly reveals that return volatilities are higher in EMs than in DMs in the sample period. The means of all the returns with the exception of Japan's Nikkei-225 index are positive and small compared to the standard deviations. The return distributions are negatively skewed for both markets except for China's SSEC index. Negative skewness implies that negative returns are more common than positive returns. Analysis on the third moment has been neglected in the literature until recently. To account for both the skewness and excess kurtosis in returns, studies have shown that MGARCH models can be combined with a multivariate density for the innovations which are skewed and have fat tails [see, Bauwens and Laurent (2005) for the multivariate skew-Student's t density model]. The difference between the maximum and minimum returns for the SSECI (71.565 to -22.629) is the highest among all the markets considered, which implies that the SSECI experienced large fluctuations compared to the others. Using the coefficient of variation (C.V.) (Std. Dev. divided by the mean return) the degree of risk in relation to the mean return is lowest for Nikkei-225 and highest for Hang-Seng. The large Jarque Bera (JB), kurtosis and skewness statistics for EMs indicate that the returns are not normally distributed.

Figure 2: Emerging and Developed Markets Weekly Log-Returns (1994–2016)



The kurtosis which measures the magnitude of extremes is very high for DMs as the value is higher than that of EMs, except for the SSEC index (and to a lesser degree, the NSEASI) and are much larger than 3. The West and Cho's (1995) modified Q algorithm tests for 10th and 20th-order serial correlation in returns and reveal no evidence of returns autocorrelation for most of the series with the exception of Nigeria's NSEASI.

Table 2: Unit Root Tests With and Without Structural Break Results

Test	NSEASI	BVSP	SSECI	Hang-Seng	Nikkei	FTSE	DJIA	DAX
				Tests Without Structural Break				
ADF	-10.2818**	-10.9855**	-12.2413**	-12.5357**	-12.8076**	-14.1798**	-13.7069**	-12.6149**
				Test With Structural Break				
ZA	-11.4545**	-12.4146**	-13.5299**	-13.3891**	-13.7368**	-14.3385**	-14.6351**	-13.1846**
T_B	2008:3:10	1998:9:14	2007:10:15	1997:8:11	2012:8:06	2009:3:09	2009:3:09	2003:3:17

Note: Superscripts **,* indicate significance levels at 1% and 5% respectively. The T_B is the break date. The tests for unit root are conducted in levels and the null hypothesis for ADF test is that the time series has unit root (i.e. is not stationary).

Figure 2 shows return dynamics revealing significant movements during the GFC period and previous financial cises. All the graphs show varying levels of fluctuation with several large outliers (of both signs) mixed in. There are periods of relative calm (early-2000s) with the period of much higher variability from 2007 to 2009. Volatility clustering of the return series is also quite evident. Table 2 presents unit root test results with and without structural breaks calculated using ADF and ZA's (1992) test regressions. The ADF test results for both EMs and DMs reveal that the returns are all stationary. Furthermore, the ZA's unit root test with breaks in both the intercept and trend focus on examining stationarity in the presence of structural breaks in mean rather than in the variance. Test results in Table 2 reveal that all the return series are stationary. This is expected due to the well known characteristics and properties of returns. The series are obviously not trending. Thus, the null hypothesis of unit root in the presence of breaks is rejected and we conclude that there are no unit roots in the returns. Usually if the variables cross their mean level, say twelve times, unit root tests will find significant mean reversion and hence conclude that they are stationary. A stationary state is one that is not changing with time even though it is not static.

4.2 Inclan and Tiao's Variance Breaks Detection Test Result

The ICSS algorithm identifies variance breaks using a nested search procedure. By construction, these identified break points in Table A1 (see, Appendices) are all significant at the 5% level. With 7 breaks for Nigeria's NSEASI and Brazil's BVSP return, the ICSS statistic finds 8 segments with statistically significant different variances from their neighbours. Eleven (11) breaks are identified for the Hang-Seng and DJIA returns, 12 breaks for SSECI return, 9 breaks for German DAX-30 return, 10 breaks for FTSE-100 return and 5 breaks for Nikkei-225 return respectively. Kang *et al.* (2009) argue that breaks in financial returns could be mainly due to global/domestic financial market and political events. Also, significant shifts in market fundamentals often serve as key source of breaks in financial and economic time series. From Table A1, a substantial number of breaks were identified in the period from 2007–2009 coinciding with the GFC and the 2001–2002 recession mainly experienced by industrialised economies.

4.3 Discussion of Estimation Results

In deciding on a model for the mean, we employ the AIC (Akaike information) and SBC (Schwarz Bayesian) VAR lag selection criteria. Even though these selection criteria assume homoscedastic residuals, implying that they could only offer a rough guide to lag length, we will estimate the mean model with 1 lag. Table 3 present estimates of fitted DVECH model for both EMs, DMs and for combined markets, which assumes that $\mathbf{A}$ and $\mathbf{B}$ are diagonal. The variances and covariances are estimated separately and the correlation coefficients are time varying. According to Bollerslev *et al.* (1988) this assumes that agents update their estimates of the means and covariances of returns each period using the newly revealed surprises in the last period's asset returns. All the ARCH and GARCH terms for DMs are highly statistically significant and most of the ARCH terms for EMs are significant with the exception of $\alpha_{2,1}$, $\alpha_{3,1}$ and $\beta_{3,1}$. The log-likelihood of the DVECH model for EMs of -8467.9255 is higher than that of CCC-MGARCH model. Some drawbacks of the DVECH models include: (1) their parameterisation do not enforce positive-definiteness and (2) they do not allow for more complicated interactions among variables; for instance, shocks in one market could have spillover effect on another market (the main focus of this paper) which is precluded by the structure of the DVECH model where the only determinant of the variance of one series are its own shocks (Doan, 2013).

The log-likelihood from the DVECH model in Table 3 for DMs of -7379.4109 is higher than the CCC-MGARCH model' in Table 4 suggesting that the CCC assumption of the conditional variances can be rejected in modelling the interaction of the 3 DM returns. Table 3 (Column 4) presents estimate of DVECH model for 2 EMs and 1 developed market. We alter the numbering by letting $i = 1, 2, 3$ represent NSEASI, DJIA and Hang-Seng returns respectively. This is done to link EMs to the USA' DJIA. We select the DJIA to represent the DMs because the financial crisis started as a US phenomenon before becoming a GFC and the US equity markets are the largest in the world. Most of the ARCH and GARCH coefficients are statistically significant.

The multivariate ARCH test is an LM test for ARCH effects in a set of series computed by regressing the cross-products of the series on a constant and its lag(s) by testing the coefficients on the lags. The result overwhelmingly rejects the lack of ARCH effect for both EMs and DMs. However, the diagonal models such as DVECH model ignore the covariances and separately model the variance using univariate estimation techniques. That is why the point estimates are often almost identical estimates from separate univariate models except that the parameters are jointly estimated to the extent that none are considered converged until all achieve convergence which result in slight differences in the estimates.

Table 3: Diagonal VECH Estimates for Emerging & Developed Stock Markets

Parameter	Emerging Markets	Developed Markets	Combined Markets
Constant	0.1443 (0.0433)**	0.2145 (0.0554)**	0.1466 (0.0392)**
r_{t-1}	0.3358 (0.0324)**	-0.1423 (0.0243)**	0.3308 (0.0324)*
Constant	0.3689 (0.1117)**	0.1773 (0.0817)*	0.3043 (0.0555)**
r_{t-1}	-0.1097(0.0291)**	-0.0246 (0.0241)	-0.1196(0.0317)**
Constant	0.2352 (0.0821)**	0.3056 (0.0580)**	0.2206 (0.0959)*
r_{t-1}	-0.0463(0.0331)	-0.1452 (0.0268)**	-0.0264(0.0295)
$c_{1,1}$	0.0314 (0.0314)	0.1112 (0.0414)**	0.0406 (0.0331)*
$c_{2,1}$	-0.3174(0.2432)*	0.1022 (0.0478)*	0.0007 (0.1134)
$c_{2,2}$	0.6768 (0.3074)*	0.3906 (0.2284)	0.2073 (0.1257)
$c_{3,1}$	0.0029 (0.1016)	0.0347 (0.0167)*	0.0466 (0.1170)
$c_{3,2}$	0.1508 (0.0478)**	0.0352 (0.0215)*	0.0258 (0.0196)
$c_{3,3}$	0.1356 (0.0516)**	0.1149 (0.0361)**	0.1532 (0.0458)**
$\alpha_{1,1}$	0.3812 (0.0587)**	0.0617 (0.0129)**	0.3902 (0.0590)**
$\alpha_{2,1}$	0.0298 (0.0197)	0.0402 (0.0113)**	0.0241 (0.0317)*
$\alpha_{2,2}$	0.0974 (0.0234)**	0.0564 (0.0254)*	0.0898 (0.0446)*
$\alpha_{3,1}$	0.0200 (0.0393)	0.0593 (0.0088)**	0.0569 (0.0497)
$\alpha_{3,2}$	0.0459 (0.0103)**	0.0439 (0.0115)**	0.0595 (0.0104)**
$\alpha_{3,3}$	0.0592 (0.0122)**	0.0756 (0.0149)**	0.0661 (0.0151)
$\beta_{1,1}$	0.7147 (0.0312)**	0.9139 (0.0158)**	0.7059 (0.0328)**
$\beta_{2,1}$	-0.8564(0.0471)**	0.9194 (0.0253)**	-0.7820(0.3520)*
$\beta_{2,2}$	0.8739 (0.0342)**	0.8979 (0.0459)**	0.8734 (0.0631)**
$\beta_{3,1}$	-0.3482(1.1302)	0.9202 (0.0113)**	-0.5918(0.3562)
$\beta_{3,2}$	0.9338 (0.0089)**	0.9239 (0.0189)**	0.9208 (0.0141)**
$\beta_{3,3}$	0.9333 (0.0114)**	0.9002 (0.0177)**	0.9239 (0.0143)**
t- shape	7.2873 (0.7557)**	7.8682 (1.0801)**	7.3778 (0.7281)**
Log-likelihood	-8467.9255	-7379.4109	-7740.7672
AIC	14.8090	12.9110	13.5410
SBC	14.9190	13.0210	13.6510
Multivariate	80.1987	99.8307	125.5789
Q(10)	[0.7607]	[0.2246]	[0.0079]
Multivariate	146.100	274.450	93.140
ARCH (72)	[0.0000]	[0.0000]	[0.0476]

Note: Numbers in parentheses indicate the standard errors while numbers in square brackets represent significance levels. Superscripts **,* indicate significance at 1% and 5% levels. AIC and SBC denote Akaike and Schwarz information criteria. The coefficients for the constant at the top belong to the mean model. The DVECH model takes the form given by: $\mathbf{H}_t = \mathbf{C} + \mathbf{A} \circ (\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}) + \mathbf{B} \circ \mathbf{H}_{t-1}$ with $\circ$ as the Hadamard product. The equation can equally be specified as: $h_{ij,t} = c_{ij} + a_{ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + b_{ij}h_{ij,t-1}$. The $i = 1, 2, 3$ refer to NSEASI, BVSP and Hang-Seng indices (emerging markets) and the same numbers for developed markets representing: FTSE-100, Nikkei-225, and DJIA indices. For the combined markets, $i = 1, 2, 3$ denote NSEASI, DJIA and Hang-Seng indices respectively. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

Table 4 presents result of 3 variants of fitted CCC-MGARCH models (with and without asymmetry). The CCC-MGARCH class of models assume that the covariances are generated with a constant (but unknown) correlation and does not allow for interdependence of volatilities across different markets or assets. Let $i = 1, 2, 3$ denote NSEASI, BVSP and Hang-Seng returns (EMs) and $i = 1, 2, 3$ represent DMs: FTSE-100, Nikkei-225 and DJIA returns. The c,

α, β and γ denote the constant, lagged squared residual, lagged variance and asymmetric terms respectively. The ARCH and GARCH terms are all highly statistically significant at conventional levels for EMs and satisfy the condition: $\alpha_1 + \beta_1 < 1$. The significance of the coefficients suggest that there is evidence of conditional volatility. The value of conditional correlations among EM returns ($\rho_{2,1}, \rho_{3,1}$ and $\rho_{3,2}$) although statistically significant is low with the highest value of around 0.4325 for (Hang-Seng–BVSP correlation) compared with correlations among DMs.

For DMs, $\rho_{3,1}$ (Nikkei–FTSE correlation) is as high as 0.4955 and is statistically significant. The constant conditional correlation (CCC) matrices of the 3 models do not differ substantially from one another. It suffices to state that for DMs, the CCC-with-asymmetry model yields the lowest conditional correlation compared with the 2 other models. Furthermore, the correlations between the conditional shocks for all the 3 models are positive in the 3 cases. For EMs, only 2 out of 3 cases are positive. Both the ARCH and GARCH terms for DMs are highly statistically significant for CCC-MGARCH and CCC-with-EGARCH models respectively. The α estimates are generally smaller for DMs compared to EMs while the β tends to be smaller for EMs (short memory). The fitted CCC-with E-GARCH variance model for both EMs and DMs also reveal significant parameter estimates, albeit the log-likelihood statistics for EMs are higher than that of the CCC-MGARCH model but lower for DMs. The CCC-with-asymmetry model for EMs reveal insignificant asymmetric terms, although with a higher log-likelihood statistic than both CCC-MGARCH and CCC-with-EGARCH variance models. For DMs however, the CCC-with-asymmetry model suggests the presence of asymmetric impacts from the unconditional shocks on the conditional volatilities in all 3 markets and reveal higher log-likelihood statistic than both the CCC-with-EGARCH variance and the CCC-MGARCH models respectively.

The multivariate diagnostics in Table 4 point to the inadequacy of the fitted models, even as it is well known that the CCC-MGARCH specification does not contain information on cross-market effects. This points toward the need for a more sophisticated model than the CCC-MGARCH specification. But Laurent *et al.* (2012) argue that over calm periods, assumptions like the CCC and symmetry in the conditional variances often cannot be rejected. Tse (2000) proposes an LM test for constant correlations against an alternative that the correlation allows greater adaptation to the observed (lagged) outer product of the residuals. The test statistic under the null hypothesis is asymptotically $\chi^2(N(N-1)/2)$ and requires the fitting of a CCC-GARCH model first (Doan, 2013). From Table 4 (Columns 2 & 3), the Tse's CCC test produces a statistically insignificant result at 1% level with a $\chi^2(3)$ value of 4.5749 and 4.6829 for EMs (for CCC-MGARCH and CCC-with-EGARCH models) and 23.0226 for DMs (but significant at both 1% and 5% levels). This suggests that a more general model could fit much better than the restrictive CCC-MGARCH for DMs. Thus, based on results in Table 4, we find evidence in favour of constant correlations (CC) across selected EMs (using CCC-MGARCH and CCC-with-EGARCH models) and evidence against CC in DMs.

Frank and Hesse (2009) note that given the high volatility during the recent GFC, the assumption of CCC is often not quite realistic especially in times of stress where correlations can rapidly change. This is due to the fact that investors' risk appetite rapidly change during financial crisis when suddenly non-related asset markets feel the impact by seemingly unrelated financial shocks (Frank and Hesse, 2009). Hence, the appropriateness of the CC assumption depends on the application and period of analysis. Based on the paper's objectives, it is crucial to employ models that admit time-varying correlations. Tse (2000) suggests that the hypothesis of CC should be tested before the estimated MGARCH model can be used for inference and the drawing of economic implications and conclusions. However, caution is advised in interpreting

Table 4: CCC-MGARCH Estimates of Emerging & Developed Market Return

	Emerging Stock Markets			**Developed Stock Markets**		
Parameter	CCC-MGARCH	CCC-with EGARCH	CCC-with asymmetry	CCC-MGARCH	CCC-with EGARCH	CCC-with asymmetry
Constant	0.1584*	0.1449**	0.1834**	0.1840*	0.2019**	0.0544
	(0.0806)	(0.0065)	(0.0584)	(0.0698)	(0.0584)	(0.0598)
r_{t-1}	0.2912**	0.3137**	0.3059**	-0.1605**	-0.1652**	-0.1481**
	(0.0631)	(0.0027)	(0.0620)	(0.0298)	(0.0265)	(0.0311)
Constant	0.3084	0.3773*	0.2261	0.1511	0.1706	0.0135
	(0.1625)	(0.1609)	(0.1372)	(0.1016)	(0.0902)	(0.0809)
r_{t-1}	-0.0769*	-0.0860*	-0.0681	-0.0232	-0.0208	-0.0060
	(0.0388)	(0.0405)	(0.0379)	(0.0365)	(0.0279)	(0.0331)
Constant	0.1644	0.1792	0.0756	0.3095*	0.3328**	0.1806*
	(0.0929)	(0.1092)	(0.0897)	(0.0724)	(0.0681)	(0.0579)
r_{t-1}	-0.0348	0.0365	-0.0225	-0.2132**	-0.2067**	-0.2077*
	(0.0346)	(0.0349)	(0.0329)	(0.0346)	(0.0315)	(0.0341)
c_1	0.1851	-0.2722**	0.1825	0.321**	-0.0639*	0.3894*
	(0.0978)	(0.0595)	(0.1411)	(0.1096)	(0.0303)	(0.1810)
c_2	0.5452*	-0.1246**	0.5763	1.5812**	0.2174	1.9421**
	(0.2466)	(0.0482)	(0.3056)	(1.3709)	(0.2507)	(0.5713)
c_3	0.1166	-0.1055**	0.1920*	0.5942*	-0.0705	0.6052**
	(0.0628)	(0.0278)	(0.0834)	(0.2376)	(0.0462)	(0.1816)
α_1	0.3779**	0.5734**	0.4514*	0.1052*	0.1956**	0.0041
	(0.0848)	(0.0754)	(0.1228)	(0.0393)	(0.0587)	(0.0199)
α_2	0.1231*	0.2501*	0.1079	0.1114**	0.2585*	-0.0269
	(0.0238)	(0.0640)	(0.0290)	(0.0719)	(0.1030)	(0.0178)
α_3	0.0789**	0.1713**	0.0265*	0.1778**	0.3148**	-0.0100
	(0.0212)	(0.0406)	(0.0131)	(0.0592)	(0.0927)	(0.0195)
β_1	0.6892**	0.9140**	0.6916**	0.8355**	0.9466**	0.8243**
	(0.0532)	(0.0284)	(0.0542)	(0.0426)	(0.0173)	(0.0606)
β_2	0.8554*	0.9762**	0.8492**	0.7120*	0.8058**	0.6781**
	(0.0269)	(0.0128)	(0.0339)	(0.2001)	(0.1384)	(0.0728)
β_3	0.9127**	0.9868**	0.9067**	0.7096**	0.8895**	0.7332**
	(0.0201)	(0.0077)	(0.0215)	(0.0872)	(0.0540)	(0.0596)
γ_1	–	–	-0.1582	–	–	0.1785**
			(0.1150)			(0.0721)
γ_2	–	–	0.0392	–	–	0.2369**
			(0.0407)			(0.0603)
γ_3	–	–	0.0966*	–	–	0.2881**
			(0.0382)			(0.0701)
$\rho_{2,1}$	-0.0289	-0.0346	-0.0300	0.4955**	0.5008**	0.4741**
	(0.0332)	(0.0285)	(0.0305)	(0.0298)	(0.0285)	(0.0249)
$\rho_{3,1}$	0.0409	0.0349	0.0407	0.4291**	0.4351**	0.4106**
	(0.0371)	(0.0288)	(0.0321)	(0.0362)	(0.0364)	(0.0328)
$\rho_{3,2}$	0.4325**	0.4371**	0.4248**	0.2868**	0.2966**	0.2837**
	(0.0310)	(0.0209)	(0.0312)	(0.0409)	(0.0371)	(0.0345)
Log-likelihood	-8601.421	-8589.555	-8588.430	-7578.819	-7579.523	-7523.497
AIC	15.0300	15.0090	15.0120	13.2460	13.2480	13.1550
SBC	15.1090	15.0880	15.1040	13.3260	13.3270	13.2480
Tse's CCC	4.5749	4.6829	9.8009	23.0226	46.6922	33.0357
test $\chi^2(3)$	[0.2057]	[0.1965]	[0.0203]	[0.0000]	[0.0000]	[0.0000]

Note: Numbers in parentheses indicate the standard errors while numbers in square brackets represent significance levels. Superscripts **,* indicate significance at 1% and 5% levels. AIC and SBC denote Akaike and Schwarz information criteria. The $i = 1, 2, 3$ refer to NSEASI, BVSP and Hang-Seng indices (emerging markets) and $i = 1, 2, 3$ for developed markets represent: FTSE-100, Nikkei-225 and DJIA indices. The CCC-MGARCH model is defined by $h_{it} = \alpha_0 + \sum_{j=1}^{q} \alpha_{ij}\varepsilon_{i,t-j}^2 + \sum_{j=1}^{p} \beta_{ij}h_{i,t-j}$. In the CCC-MGARCH model, $\mathbf{H}_t = \mathbf{D}_t\mathbf{R}\mathbf{D}_t$ where $\mathbf{D}_t$ =diag$(h_{11t}^{0.5}, ..., h_{mmt}^{0.5})$ and $\mathbf{R} = [\rho_{ij}]$ is the correlation matrix, so that $h_{ij,t} = \rho_{ij}(h_{ii,t}h_{jj,t})^{0.5}$ for $i, j = 1, ..., m$. Each conditional variance $h_{jj,t}, j = 1, ..., m$, follows a basic univariate GARCH model. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

the test result as it is sensitive to sample size. Tse's Monte Carlo experiments show that the test has the appropriate size for sample length of 1000 or above and is robust against nonnormality but tends to over-reject the null hypothesis in smaller samples (the problem of over-rejection diminishes with increase in the sample size).

Table 5: CCC-MGARCH(Spillover) Estimates (Emerging & Developed Markets)

	Emerging Stock Markets		**Developed Stock Markets**	
Parameter	CCC (spillover variances)	CCC (spillover variances) (t-dist)	CCC (spillover variances)	CCC (spillover variances) (t-dist)
Constant	0.1493 (0.9482)	0.1495** (0.0516)	0.1804* (0.0749)	0.2017** (0.0494)
r_{t-1}	0.2721 (1.1559)	0.3338** (0.0353)	-0.1622** (0.0290)	-0.1611** (0.0247)
Constant	0.2727 (0.2652)	0.3597** (0.1141)	0.1321 (0.1103)	0.1321 (0.0869)
r_{t-1}	-0.0752* (0.0096)	-0.1028* (0.0316)	-0.0305 (0.0311)	-0.0285 (0.0295)
Constant	0.1556 (4.7570)	0.1909* (0.0846)	0.3260** (0.0687)	0.3155** (0.0561)
r_{t-1}	-0.0425 (3.3853)	-0.0340 (0.0324)	-0.2159** (0.0308)	-0.2011** (0.0315)
c_1	0.1524 (0.1254)	0.0346 (0.0338)	0.3312* (0.1578)	0.2088** (0.0698)
c_2	0.6454 (4.3537)	0.4933** (0.1850)	1.3451 (0.9236)	0.5430* (0.2152)
c_3	0.0900 (0.9363)	0.1245* (0.0544)	0.5773** (0.2042)	0.2716* (0.1245)
$\alpha_{1,1}$	0.3828 (0.5192)	0.3829** (0.0654)	0.1009** (0.0242)	0.0719 (0.0175)
$\alpha_{1,2}$	0.0733 (0.0584)	0.0103 (0.0244)	0.0007 (0.0291)	-0.0169 (0.0158)
$\alpha_{1,3}$	0.0018** (0.0000)	-0.0043 (0.0218)	0.0120 (0.0289)	-0.0062* (0.0134)
$\alpha_{2,1}$	-0.0613 (1.7897)	-0.0495 (0.0418)	-0.0578 (0.0398)	-0.0437 (0.0237)
$\alpha_{2,2}$	0.1313 (0.2857)	0.1031** (0.0214)	0.1004* (0.0477)	0.0597** (0.0215)
$\alpha_{2,3}$	-0.0206 (0.1280)	-0.0547** (0.0215)	0.0791 (0.0474)	0.0382 (0.0248)
$\alpha_{3,1}$	0.0212 (0.9616)	0.0079 (0.0233)	0.0271 (0.0383)	0.0151 (0.0235)
$\alpha_{3,2}$	0.0019 (0.0396)	-0.0036 (0.0132)	-0.0268 (0.0383)	-0.0409 (0.0211)
$\alpha_{3,3}$	0.0713 (0.5106)	0.0647** (0.0151)	0.1748** (0.0496)	0.0933** (0.0295)
β_1	0.6991** (0.0314)	0.7138** (0.0344)	0.8319** (0.0528)	0.8955** (0.0241)
β_2	0.8458** (0.0148)	0.8939** (0.0238)	0.7512** (0.1373)	0.8858** (0.0362)
β_3	0.9195** (0.1082)	0.9302** (0.0145)	0.7139** (0.0737)	0.8565** (0.0477)
$\rho_{2,1}$	-0.0280 (0.4367)	-0.0379 (0.0263)	0.4921** (0.0292)	0.4779** (0.0232)
$\rho_{3,1}$	0.0402** (0.0503)	0.0312 (0.0267)	0.4265** (0.0332)	0.4176** (0.0298)
$\rho_{3,2}$	0.4328 (0.2273)	0.4364** (0.0252)	0.2781** (0.0363)	0.2524** (0.0328)
t- shape	–	7.1058** (0.7789)	–	7.1478* (0.8132)
Log-likelihood	–8588.5138	–8487.4124	–7574.4624	–7466.3471
AIC	15.0170	14.8430	13.2490	13.0630
SBC	15.1230	14.9530	13.3550	13.1720
Tse's CCC	9.9864	9.2576	14.6870	12.1740
$\chi^2(3)$ test	[0.0187]	[0.0261]	[0.0021]	[0.0068]

Note: Numbers in parentheses indicate the standard errors while those in square brackets represent significance levels. Superscripts **,* indicate significance at 1% and 5% levels respectively. AIC and SBC denote Akaike and Schwarz information criteria. The $i = 1, 2, 3$ refer to NSEASI, BVSP and Hang-Seng indices (emerging markets) and $i = 1, 2, 3$ for developed markets represent: FTSE-100, Nikkei-225 and DJIA indices. The CCC-GARCH with spillover variances which allows for greater interactions by adding spillover terms to the variance calculation can be expressed as $h_{ii,t} = c_{ii} + \sum_j \alpha_{ij}\varepsilon^2_{j,t-1} + \beta_i h_{ii,t-1}$. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

Table 5 presents result from fitted CCC-MGARCH-with-spillover model under 2 error assumptions– Gaussian and Student's-t. The model has the same number of free parameters (21) with the DVECH model, provides greater flexibility in the variances but less so in the covariances. The GARCH terms are all highly statistically significant at the 1% level. The significance of the coefficients suggest evidence of conditional volatility. The correlations among EM returns ($\rho_{2,1}, \rho_{3,1}$ and $\rho_{3,2}$), although mostly significant, are often lower than that of CCC-MGARCH model of Table 5, while significantly higher for DMs. The diagnostics in Table 5 reflect the model's adequacy or otherwise. The CCC assumption can therefore be rejected for both emerging and advanced markets. The Tse's CCC test reveals a statistically significant result at the 5% level with a $\chi^2(3)$ value of 9.9864 for the CCC-MGARCH-with-spillover effect for EMs while Tse's CCC test for model with spillover effect (with t-distribution) reveals a $\chi^2(3)$ value of 9.2576 for EMs and 14.6870 for DMs at 1% level (with Gaussian distribution). The test further confirms that a more general model could fit better than the restrictive CCC-MGARCH specification. Due to some shortcomings of Tse's CCC test emanating from their inability to generalise well to higher dimensions, Engle (2001) propose a test that only requires consistent estimate of the CCC to be implemented using a VAR model.

To examine the interdependence of volatilities across different markets and to capture asymmetric behaviour of unconditional shocks on the conditional volatility, 2 variants of CCC-VARMA-MGARCH models (with and without asymmetry) are fitted and the result is presented in Table 6. The CCC-VARMA-MGARCH specification is an extension of the CCC-MGARCH (spillover) model and includes β coefficients on all lagged variances and not just the own variances as in CCC-MGARCH (spillover) model. For EMs, estimates of the constant, ARCH and GARCH terms are all significant at conventional levels (for CCC-VARMA-MGARCH model). Also, estimates of the effects of lagged own and cross innovations and lagged own and cross volatility on the present own and cross volatility is also presented. Consistent with extant literature, own-volatility spillovers are to a large extent higher than cross-volatility spillovers especially for the selected EMs while these tend to be negative for DMs. Furthermore, for DMs, past shocks to volatility and lagged GARCH terms are significant in all markets for CCC-VARMA-MGARCH model.

Results from the CCC-VARMA-AMGARCH model are presented in Table 6 (Columns 3 & 5). This more sophisticated model incorporates asymmetric effects allowing for different responses to past positive and negative shocks to volatility. The intercept terms of the model for DMs are mostly highly statistically significant at 1% and 5% levels and the asymmetric terms are equally significant except for γ_3. The CCC-VARMA-AMGARCH model for DMs detect significant positive asymmetric effect except for γ_1 and γ_2. This suggests that a positive shock has a greater impact on conditional variance than a negative shock. The γ estimates are mostly insignificant for EMs (with the exception of γ_3) so that the CCC-VARMA-MGARCH specification is preferred compared to the CCC-VARMA-AMGARCH model on the basis of the log-likelihood value and smaller AIC and SBC. Both CCC-VARMA-MGARCH and CCC-VARMA-AMGARCH models suggest existence of cross-market effects for DMs and weak effects for EMs. Additionally, the CCC-VARMA-AMGARCH model did not detect substantial presence of asymmetric behaviour in EMs. For the conditional correlation estimates, results reveal that DMs exhibit higher correlations compared with EMs while the CCC-VARMA-AMGARCH model captures higher correlations compared with CCC-VARMA-MGARCH model. The conditional correlations between Nikkei-225 and FTSE-100 markets is the highest while the DJIA–Nikkei-225 conditional correlations is the lowest behind DJIA–FTSE-100 correlations. Our finding on the DJIA–Nikkei relationship vary with many of the results presented in the literature that analyse these markets which find high correlation among the markets. The use of different market indices, period of analysis and methodologies are largely responsible for the difference in findings.

Table 7 presents estimate of a trivariate VAR-EGARCH model. The model allows for spillover effect from the lagged ε_j to the variance of i. In the case of the mean equation, we employ the same model form for each variable, but in the overall estimation we estimate both the VAR and GARCH parameters simultaneously. The parameter vectors for the regression coefficients are set up in $\boldsymbol{\beta}$. Thus, β_1 is the coefficient vector for the first VAR equation (for Nigeria based on our ordering for EMs), with $\beta_{1,1}$ the coefficient on the constant in that

Table 6: CCC-VARMA and AGARCH Estimates (With & Without Asymmetry)

	Emerging Stock Markets		Developed Stock Markets	
Parameter	CCC-VARMA MGARCH	CCC-VARMA AMGARCH	CCC-VARMA MGARCH	CCC-VARMA AMGARCH
Constant	0.1602**(0.0422)	0.2004**(0.0539)	0.1819**(0.0568)	0.0287 (0.0559)
r_{t-1}	0.3239**(0.0315)	0.3121**(0.0288)	-0.1760**(0.0247)	-0.1213**(0.0286)
Constant	0.3671 (0.1041)	0.1747 (0.1153)	0.1411 (0.0777)	-0.0244 (0.0830)
r_{t-1}	-0.1067*(0.0262)	-0.0681*(0.0312)	-0.0324 (0.0263)	-0.0041 (0.0297)
Constant	0.1841*(0.0776)	0.0523 (0.0847)	0.3042**(0.0567)	0.1869**(0.0587)
r_{t-1}	-0.0328 (0.0254)	-0.0239 (0.0298)	-0.2036 (0.0268)	-0.1915**(0.0327)
c_1	0.0804 (0.0616)	0.3064 (0.0475)**	-1.8693 (0.5097)**	0.1010 (0.1377)
c_2	0.3053 (0.1817)	0.3589 (0.1595)*	-0.0478 (0.5363)	1.7540 (0.5185)**
c_3	0.1345 (0.0603)*	0.2051 (0.0892)*	0.6694 (0.2295)**	0.5704 (0.2853)*
$\alpha_{1,1}$	0.3664 (0.0473)**	0.3931 (0.0384)**	-0.0173 (0.0173)	0.0173 (0.0176)
$\alpha_{1,2}$	0.0139 (0.0144)	0.0302 (0.0102)**	0.0128 (0.0139)**	-0.0554(0.0149)**
$\alpha_{1,3}$	0.0005 (0.0198)	-0.0074 (0.0178)	0.0297 (0.0161)	-0.0112 (0.0169)
$\alpha_{2,1}$	-0.0405 (0.0384)	-0.0287 (0.0341)	-0.0616 (0.0371)	-0.1361 (0.0492)**
$\alpha_{2,2}$	0.0989 (0.0212)**	0.1035 (0.0165)**	0.0636 (0.0255)*	0.0023 (0.0241)
$\alpha_{2,3}$	-0.0809 (0.0261)**	-0.0612 (0.0155)**	0.0311 (0.0291)**	0.0687 (0.0329)*
$\alpha_{3,1}$	0.0107 (0.0209)	-0.0063 (0.0218)	-0.0134 (0.0130)	-0.0392 (0.0351)
$\alpha_{3,2}$	-0.0092(0.0149)	0.0004 (0.0131)	-0.0034 (0.0091)	-0.0540 (0.0287)**
$\alpha_{3,3}$	0.0631 (0.0163)**	0.0327 (0.0205)	0.0686 (0.0141)**	0.0148 (0.0420)
$\beta_{1,1}$	0.7072 (0.0332)**	0.7279 (0.0229)**	-2.0569 (0.1179)**	0.8034 (0.1315)**
$\beta_{1,2}$	0.8339 (0.8186)	22.8714(10.3119)*	-0.0755 (0.5991)	0.1645 (0.1163)
$\beta_{1,3}$	1.1361 (1.0870)	1.0428 (0.7248)**	8.1791 (1.0189)**	0.0327 (0.2489)**
$\beta_{2,1}$	0.4181 (0.4669)	5.3056 (3.9327)	-0.9794(1.1459)	0.4627 (0.4255)
$\beta_{2,2}$	0.8668 (0.0302)**	0.8505 (0.0228)**	0.7894 (0.1054)**	0.6017 (0.1237)**
$\beta_{2,3}$	0.1765 (0.0783)*	0.1430 (0.0714)*	2.7769 (2.8988)	-0.3100(0.5706)
$\beta_{3,1}$	-0.2368 (0.2852)	-0.0560 (0.1833)	1.6937 (0.2989)**	1.2961 (0.3812)**
$\beta_{3,2}$	0.0071 (0.0226)	0.0549 (0.0290)	0.0211 (0.3604)	-0.3559 (0.4011)
$\beta_{3,3}$	0.9349 (0.0210)**	0.8689 (0.0257)**	0.0096 (0.0897)	0.3175 (0.1375)*
γ_1	–	-0.1284 (0.0472)	–	0.1670 (0.0313)**
γ_2	–	0.0307 (0.0177)	–	0.2362 (0.0497)**
γ_3	–	0.0977 (0.0225)**	–	0.3171 (0.0504)
$\rho_{2,1}$	-0.0351(0.0298)	-0.0027 (0.0013)*	0.4877 (0.0259)**	0.4766 (0.0227)**
$\rho_{3,1}$	0.0348 (0.0259)	0.0546 (0.0273)*	0.4445 (0.0268)**	0.4146 (0.0265)**
$\rho_{3,2}$	0.4410 (0.0256)**	0.4339 (0.0242)**	0.2608 (0.0306)**	0.2748 (0.0264)**
t- shape	7.3883 (0.7416)**	–	–	–
Log-likelihood	–8479.4911	–8566.1028	–7453.0968	–7499.8059
AIC	14.8400	14.9940	13.0500	13.1350
SBC	14.9760	15.1390	13.1860	13.2800
Tse's CCC	9.8731	10.4274	12.4569	14.8466
test $\chi^2(3)$	[0.0196]	[0.0153]	[0.0059]	[0.0019]

Note: Numbers in parentheses indicate the standard errors while numbers in brackets represent significance levels. Superscripts **,* indicate significance levels at 1% and 5%. AIC and SBC stand for Akaike and Schwarz information criteria. The $i = 1, 2, 3$ refer to NSEASI, BVSP and Hang-Seng Indices (emerging markets) and the same numbers for developed markets representing: FTSE-100, Nikkei-225, and DJIA Indices. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

equation. In terms of guess values, the lagged log-variance coefficient is initialised to 0.8 with the variance intercept set to give almost the observed variance when combined with that. The α's are initialised to zero on all but the own effect (which is set equal to 0.25) and the asymmetry coefficients are zeroed out. The conditional variance of the return in each market is a logarithmic function of past own and cross-market standardised innovations. If α_{ij} is positive, the impact of $z_{j,t-1}$ on $\log h_{it}$ will be positive (negative) if the magnitude of $z_{j,t-1}$ is greater (smaller) than its expected value $(2/\pi)^{0.5}$. Volatility spillovers across markets are measured by α_{ij}. A significant positive α_{ij} coupled with a negative d_j implies that negative innovations in market j have a higher impact on the volatility of market i than positive innovations.

Table 7: VAR-EGARCH Model with Spillover and Asymmetry

Parameter	Emerging Markets	Developed Markets	Combined Markets
$\beta_{1,1}$	0.1490 (0.0306)**	-0.0304 (0.0600)	0.1278 (0.028)**
$\beta_{1,2}$	0.3332 (0.0238)**	-0.1394(0.0327)**	0.3290 (0.0231)**
$\beta_{1,3}$	0.0067 (0.0057)	-0.0294 (0.0218)	0.0103 (0.0095)
$\beta_{1,4}$	0.0112 (0.0067)	0.3644 (0.0296)**	0.0104 (0.0058)**
$\beta_{2,1}$	0.1861 (0.0889)*	-0.0653(0.0856)	0.1033 (0.0356)**
$\beta_{2,2}$	-0.0017 (0.0321)	0.1006 (0.0458)*	0.0109 (0.0176)
$\beta_{2,3}$	-0.0657 (0.0244)**	-0.0764(0.0352)*	-0.0666(0.0243)**
$\beta_{2,4}$	0.0788 (0.0346)*	0.3317 (0.0409)*	0.0653 (0.0171)**
$\beta_{3,1}$	-0.0054 (0.0662)	0.1501 (0.0607)*	-0.0421 (0.0667)
$\beta_{3,2}$	0.0321 (0.0266)**	0.1297 (0.0349)**	0.0276 (0.0260)
$\beta_{3,3}$	0.0714 (0.0178)**	-0.0163(0.0224)	0.3640 (0.0332)**
$\beta_{3,4}$	-0.0331(0.0272)	-0.0945(0.0315)**	-0.0539 (0.0281)
c_1	0.1884 (0.0058)**	0.0868 (0.0155)**	0.1645 (0.0061)**
c_2	0.0709 (0.0024)**	0.2974 (0.0636)**	0.1267 (0.0039)**
c_3	0.0596 (0.0022)**	0.1489 (0.0263)**	0.0836 (0.0037)**
g_1	0.9107 (0.0041)**	0.9403 (0.0103)**	0.9252 (0.0041)**
g_2	0.9748 (0.0008)**	0.8559 (0.0312)**	0.9130 (0.0027)**
g_3	0.9738 (0.0009)**	0.8966 (0.0180)**	0.9607 (0.0016)**
$\alpha_{1,1}$	0.5868 (0.0180)**	0.1141 (0.0267)**	0.6139 (0.0200)**
$\alpha_{1,2}$	0.1141 (0.0168)**	0.0071 (0.0187)	-0.0388 (0.0036)**
$\alpha_{1,3}$	-0.0125 (0.0153)	0.0551 (0.0159)**	0.0882 (0.0134)**
$\alpha_{2,1}$	-0.0402 (0.0125)*	0.0561 (0.0197)**	-0.0098 (0.0192)
$\alpha_{2,2}$	0.1912 (0.0181)**	0.1685 (0.0439)**	0.0649 (0.0043)**
$\alpha_{2,3}$	0.1019 (0.0114)	-0.0013(0.0205)	0.1161 (0.0198)**
$\alpha_{3,1}$	-0.0111 (0.0124)	0.1086 (0.0265)**	-0.0458 (0.0178)*
$\alpha_{3,2}$	0.0904 (0.0221)**	-0.0141(0.0265)	0.0057 (0.0043)
$\alpha_{3,3}$	0.1422 (0.0121)**	0.1254 (0.0369)**	0.1725 (0.0167)**
d_1	0.0928 (0.0263)**	-0.9255(0.2556)**	0.0797 (0.0244)**
d_2	0.0349 (0.0416)	-0.6628(0.1891)**	-2.8803 (0.1528)**
d_3	-0.6446 (0.0790)**	-1.0387(0.3703)**	-0.4580 (0.0667)**
$\rho_{2,1}$	-0.0413 (0.0274)	0.4499 (0.0241)**	0.0206 (0.0304)
$\rho_{3,1}$	0.0317 (0.0268)	0.3816 (0.0231)**	0.0405 (0.0280)
$\rho_{3,2}$	0.4364 (0.0184)**	0.2466 (0.0263)**	0.2706 (0.0235)**
Log-likelihood	-8548.7911	-7402.2864	-7760.6967
AIC	14.9640	12.9650	13.5900
SBC	15.1090	13.1100	13.7350

Note: Numbers in parentheses indicate the standard errors. Superscripts **,* indicate significance levels at 1% and 5%. AIC and SBC stand for Akaike and Schwarz information criteria. The $i = 1, 2, 3$ refer to NSEASI, BVSP and Hang-Seng indices (emerging markets) and the same numbers for developed markets represent FTSE-100, Nikkei-225, and DJIA indices. For combined markets $i = 1, 2, 3$ refer to NSEASI, DJIA and Hang-Seng indices. For the combined markets, $i = 1, 2, 3$ denote NSEASI, DJIA and Hang Seng indices respectively. The mean specification for the VAR-EGARCH model is: $r_{i,t} = \beta_{i,1} + \sum_{j=1}^{3} \beta_{ij} r_{j,t-1} + \varepsilon_{i,t}$ for $i, j = 1, 2, 3$. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

Volatility persistence measured by g_i is in all cases high and close to unity. However, the degree of persistence is higher in EMs compared with DMs. The contemporaneous relationship between returns of the markets is captured by the conditional covariance. The correlation structure is often the most important feature and characteristic for analysing the potential for diversification for investors and portfolio managers. Koutmos' covariance specification implies that the correlation of the returns of markets is constant. For DMs, all the asymmetry terms (the d's) are highly significant and the off-diagonal α's are of the expected sign and equally highly significant. The estimated conditional pairwise correlations are substantially lower in EMs compared with DMs. For example, for EMs, Hang-Seng–NSEASI correlation is 0.0317 while correlation between BVSP and NSEASI is negative (-0.0413). For DMs, the Nikkei-225–FTSE-100 correlation is the highest (0.4499) followed by the DJIA–FTSE-100 correlation. This implies that there is less potential for diversification among DMs and that EMs can offer portfolio diversification opportunities both among them and for DM investors.

For the fitted VAR-EGARCH model (for EMs), the log-likelihood is -8548.7911 which is larger than that of CCC-MGARCH-with-spillover variance model (-8588.5138), CCC-MGARCH (-8601.421), CCC-with-EGARCH (-8589.555) and CCC-with-asymmetry (-8588.430) models. For DMs, the corresponding log-likelihood is -7402.2864 which is larger than the CCC-with-spillover variance' (-7574.4624), CCC-MGARCH (-7578.819), CCC-with-EGARCH (-7579.523) and CCC-with-asymmetry (-7523.497) models. Among all the fitted MGARCH models, the closest model type to the VAR-EGARCH specification is the aymmetric-CCC-with-spillover variances model. It has the same number of free parameters with the VAR-EGARCH but the variances are specified in the standard additive form and the asymmetry term does not enter the spillover terms. There is still no consensus in the literature about whether the superior fit in VAR-EGARCH models is as a result of the exponential specification or due to the incorporation of asymmetric terms into the spillover.

Table A2 (see Appendices) present estimates of trivariate BEKK-MGARCH and BEKK-AMGARCH models (with and without asymmetry) for the selected EMs and DMs. For the results in Table A2 (Columns 6 & 7), $i = 1, 2, 3$ refer to NSEASI, DJIA and Hang-Seng returns. The BEKK-MGARCH model proposed by Engle and Kroner (1995) allows for greater interactions. Studies have shown that this model sometimes encounter the challenge of negative parameters. For the c_i coefficients, the estimated parameters for EMs are all positive while some coefficients in the case of DMs are negative. For results in Columns 6 & 7 while $c_{2,1}$ is negative (for both BEKK-MGARCH and BEKK-AMGARCH), $c_{2,2}$ is equally negative for DMs (NSEASI, DJIA and Hang-Seng indices). Conversely $c_{3,2}$ is positive for BEKK-AMGARCH model (Table A2, Column 5). This is because it is a factor of the variance intercept, rather than the variance itself, the coefficients other than 1,1 do not have simple interpretations (Doan, 2013).

We find that the conditional variances for EMs (Table A2, Column 2) are directly affected by their past news and volatility only with respect to coefficients $\alpha_{1,1}$, $\alpha_{2,1}$, $\alpha_{2,2}$ and $\alpha_{3,3}$ which are statistically significant at 1% and 5% levels. On the effects of past conditional variances on conditional variances, $\beta_{1,1}$, $\beta_{2,1}$, $\beta_{2,2}$ and $\beta_{3,3}$ are statistically significant while only $\gamma_{3,2}$ and $\gamma_{3,3}$ are significant for BEKK-AMGARCH specification. The log-likelihood value for the BEKK-AMGARCH model is higher (-8561.906) than that of BEKK-MGARCH model (-8607.514). On the BEKK-AMGARCH model results for DMs, we find that not only are their conditional variances directly affected by their own volatility and news, but also by bi-directional transmission of volatility and shock between each other (except for insignificant $\alpha_{2,1}$, $\alpha_{2,2}$, $\alpha_{2,3}$ and $\alpha_{3,1}$ coefficients). For the β coefficients (which measure the effects of past conditional variances on conditional variances) it is only $\beta_{2,3}$ and $\beta_{3,1}$ that are insignificant.

On the results in Table A2 (Columns 6 & 7) (NSEASI, DJIA and Hang-Seng), their conditional variances are directly affected by their past news and volatility except with respect to coefficients $\alpha_{1,2}$, $\alpha_{1,3}$, $\alpha_{2,1}$, $\alpha_{2,3}$ and $\alpha_{3,1}$ respectively which are statistically insignificant. Relative to Nigeria's NSEASI, we find that it is now affected by its own volatilities and shocks lagged one period and indirectly by Hang-Seng and DJIA return shocks. The β coefficients (Table A2, Column 7) i.e. for BEKK-AMGARCH models are mostly insignificant except for $\beta_{2,2}$ and $\beta_{3,3}$. The asymmetric terms with the exception of $\gamma_{1,2}$ and $\gamma_{3,3}$ are highly significant. The log-likelihood for the BEKK-AMGARCH specification for combined markets is higher (-7798.384) than BEKK-MGARCH's (-7878.433) while the relevant information criteria are lower in the BEKK-AMGARCH specification than in the corresponding BEKK-MGARCH equation. Figure 5 (see Appendices) shows the variances (diagonal) and correlations (off-diagonal) estimates for 3 EMs: NSEASI, BVSP and Hang-Seng and 3 DMs: FTSE-100, Nikkei-225 and DJIA returns from fitted BEKK-MGARCH model. The BVSP–Hang-Seng correlation estimate increase consistently (above 0.75 in some periods) from 1994 to 2008 while NSEASI–BVSP correlation is significantly lower hovering around 0.25, with large spikes particularly during the 2001 recession and the GFC periods. This reflect the linkages between the two markets which are modest during normal periods, but tend to be greater during periods of major global market instability. Also, the variances tend to increase during significant market events such as the GFC as can be observed in Figure A (see, diagonals chart). It suffices to state that the trend for sustained gross portfolio inflows (equity and debt) into EM averages 1.2% of EM GDP (or a cumulative total of \$1.6 trillion comprising \$989 billion for debt securities and \$590 billion for equity securities) over the past decade (Credit Suisse, 2014).

The diagonal elements of the matrix $\mathbf{A}^*$ (namely $\alpha_{1,1}$, $\alpha_{2,2}$ & $\alpha_{3,3}$) measure the effects of own past shocks on that series' own conditional variance. From Table A2 (Column 2), all estimated diagonal elements of $\mathbf{A}^*$ are statistically significant. Comparing the magnitude of the estimates of the combined markets in BEKK-MGARCH model (Table A2, Column 6), the shock of an EM (NSEASI) has the largest effect (0.6121), followed by another EM (Hang-Seng) (0.2475) on their own variance, with DM (DJIA) having the smallest own shock effect (0.2085). This suggest that past shocks play more crucial role in the volatility of EMs than those in the volatility of the DMs. This according to Li and Giles (2015) can be explained by the fact that the more advanced a market is, the less affected it is by its own past shocks. It can also imply that the EMs exhibit less market efficiency than the DMs as the effects of the shock takes a longer time to dissipate. The diagonals of the matrix $\mathbf{B}^*$ (namely $\beta_{1,1}$, $\beta_{2,2}$ & $\beta_{3,3}$) measure the effects of past volatility of a market on its conditional variance. All the estimated parameters on the diagonal of $\mathbf{B}^*$ are statistically significant at 1% level. Also, the magnitude of these estimates are very close to unity, indicating a common stylised fact of financial return data (i.e. a degree of volatility persistence). The volatility persistence tends to be lower for the EMs compared to DMs, indicating that the EMs derive less of their volatility persistence from own past volatility than do DMs.

On the asymmetric response of volatility, the diagonal elements of the matrix $\boldsymbol{\gamma}^*$ capture the asymmetric response of a given market to its own past negative shocks or bad news. From Table A2 (Columns 3, 5 & 7), the diagonal elements of the matrix $\boldsymbol{\gamma}^*$ (namely $\gamma_{1,1}$, $\gamma_{2,2}$ & $\gamma_{3,3}$) for DMs are highly significant, indicating that DMs have a more evident response to negative shocks than do EMs. The magnitude of the FTSE-100, Nikkei-225 and DJIA stock market reaction to their own negative shock is -0.2663, -0.3041 and -0.3058 respectively. For EMs with the exception of Hang-Seng, all the magnitude values are insignificant. A key objective of this paper is to uncover the extent of volatility spillovers across selected stock markets, that can be captured by the off-diagonal parameters of the matrices $\mathbf{A}^*$, $\mathbf{B}^*$ and $\boldsymbol{\gamma}^*$. First, we look at the off-diagonal elements of the matrix $\mathbf{A}^*$ for EMs (Table A2, Column 2) which indicates the overall shock spillover among NSEASI, BVSP and Hang-Seng indices. Accordingly, there are no significant shock spillovers from the NSEASI to the BVSP and Hang-Seng as both $\alpha_{1,2}$ (-0.0059) and $\alpha_{1,3}$ (0.0380) are not significant. For DMs (Table A2, Column 4) there are significant shock spillovers from the FTSE-100 to the Nikkei-225 and DJIA indices as both $\alpha_{1,2}$ (0.2727) and $\alpha_{1,3}$ (0.1592) are significantly different from zero. This indicates that the transmissions are stronger between DMs than among EMs and between DMs and EMs. Additionally, there is no sufficient evidence to show that the shocks of the Nikkei-225 index affects the volatility of the FTSE-100 and DJIA indices. This implies that there is only a weak past shock spillover between the Nikkei-225, FTSE-100 and DJIA indices. Also, there is only a weak past shock spillover from some EMs to the USA' DJIA index. This result is in line with findings from extant literature that volatility spillover effects emanate from DMs to emerging/frontier markets.

Table A3 presents estimate of trivariate BEKK-MGARCH and BEKK-AMGARCH models (with financial crisis dummies) for the selected EM and DM returns as well as for combined markets. Typically, the addition of dummies to BEKK-MGARCH specifications adjusts the C term in the GARCH recursion. This adds a coefficient for each variance equation for each of the added variables. This paper considers 18th August, 2008 as the starting point of the financial crisis and 28th September, 2009 as the ending point of the crisis. The rationale behind the selection is that even though the financial crisis became sharply out of control in the wake of the Lehman Brothers bankruptcy on 15th September, 2008, the impact had already manifested in advanced financial markets with increased delinquencies on subprime mortgages, driven by rising interest rates for refinancing and falling house prices in the USA, resulting in uncertainty in the value of many structured credit products (Frank and Hesse, 2009). For the results in Table A3 (Columns 6 & 7), the c_i coefficients, the estimated parameters for EMs are all positive while some coefficients for DMs are negative. For results in Column 7, while $c_{2,1}$ is negative, $c_{3,3}$ is positive for a mixture of selected EMs and DMs (NSEASI, Hang-Seng and DJIA indices). Conversely, $c_{3,2}$ is barely positive for BEKK-AMGARCH model.

We find that the conditional variances for EMs are directly affected by their past news and volatility only with respect to coefficients $\alpha_{1,1}$, $\alpha_{3,1}$ and $\alpha_{3,3}$ which are statistically significant at 1% level. On the effects of past conditional variances on the conditional variances, $\beta_{2,2}$ and $\beta_{3,3}$ are significant while only $\gamma_{1,1}$ and $\gamma_{3,3}$ are significant for BEKK-AMGARCH specification. The log-likelihood value for the BEKK-AMGARCH specification is higher (-7714.518) than that of BEKK-MGARCH model (-7768.775). On the BEKK-AMGARCH results for DMs, we find that, not only are conditional variances directly affected by own-volatility and news in most cases, but also by bi-directional transmission of volatility and shock between each other (except for an insignificant $\alpha_{2,1}$ coefficient). For the β coefficients (which measure the effects of past conditional variances on conditional variances) only $\beta_{3,1}$ and $\beta_{3,2}$ are significant. For EMs, most of the included dummies (August, 2008 to September, 2009) are not significant while for DM returns, most are significant. On the results in Table A2 (Column 7) comprising a mixture of EMs and DMs, all the financial crisis dummies were statistically significant.

On the results in Table A3 (Column 7) for combined markets (NSEASI, DJIA and Hang-Seng), their conditional variances are directly affected by their past news and volatility except with respect to coefficients $\alpha_{1,2}$, $\alpha_{1,3}$ and $\alpha_{2,3}$ that are not significant. Relative to Nigeria's NSEASI, we find that it is now affected by its own volatilities and previous shocks and indirectly by Hang-Seng and DJIA return shocks. The β coefficients (in Column 7) as in BEKK-MGARCH (in Column 6) are mostly insignificant with the exception of $\beta_{2,2}$ and $\beta_{3,3}$. The asymmetric terms with the exception of $\gamma_{1,1}$ and $\gamma_{1,3}$ are all highly statistically significant.

The log-likelihood for the BEKK-AMGARCH model with dummies is higher (-8462.962) than BEKK-MGARCH model with dummies (-8491.712). However, the dummy variable coefficients for the GFC in the variance and covariance equations are all insignificant for the 3 EMs (see, Table A3, Columns 2 & 3) with the exception of ($D_{GFC(1,1)}$) which is significant at 1% level. This suggests that the GFC did not influence cross-market volatility among EMs, but had slight influence on own-volatility, as in the case of ($D_{GFC(1,1)}$) which is positive. Of note is that although the GFC eventually spread to EMs, it probably did not impact significantly on cross-market volatility among these selected markets for the entire period of the inclusion of dummy variable (August, 2008 to September, 2009). In addition, such impacts contributing to rising co-volatility have probably occurred for a much longer period than the one proposed by the length of the sustained 2008 to 2009 dummy variable.

For DMs (see, Table A3, Columns 4 & 5) some of the dummy variable coefficients for the GFC in the variance and covariance equations are significant with the exception of ($D_{GFC(2,2)}$), ($D_{GFC(3,2)}$) and ($D_{GFC(3,3)}$) (From Column 5). This implies that the GFC influence cross-market volatility among DMs more than own-volatility, providing justification for the claim of the existence of spillover effect during the GFC. That is, the GFC impacts significantly on cross-market volatility among DMs and such impacts have contributed to rising positive co-volatility during the period while the negatively signed coefficients are not significant (Own-volatility spillovers indicates a one way causal relation between past volatility shocks and current volatility in the same market while cross-volatility spillovers refer to a one-way causal link between past volatility shocks in one market and current volatility in another market). Karunanayake *et al.* (2010) note that "apart from over-leveraging, a loss of confidence by investors in the value of sub-prime mortgages, a rise in defaults and under-provision for non-performing loans by the banking system and the failure of banks to manage risks can also be regarded as other relevant causes of the volatility of stock markets during the recent global crisis". Similar dummy variable specifications to the one used in this paper have been proposed in the literature by Karunanayake *et al.* (2010), among others. Finally, all the fitted BEKK specifications are stable as the sum of all the relevant matrices have eigenvalues less than unity.

In terms of estimation strategy for MGARCH models, we find that inclusion of additional flexibility in this class of models tend to substantially decrease the chance of convergence to a global maximum on carrying out the maximum likelihood procedure. The DVECH and CCC-MGARCH models are the most restrictive MGARCH models analysed in this paper, as the CCC-MGARCH for example, assumes that the correlation coefficient is constant over time. However, the relative ease with which these models were fitted compared to the more flexible BEKK-AMGARCH model provides a reasonable starting point for our multivariate volatility analysis. Furthermore, the inclusion of dummy variables impact not only the coefficients but equally adjusts the c_i term in the GARCH recursion as well. There still are concerns in the literature on the handling of dummy regressors in BEKK models due to the desire to enforce positive-definiteness and the choice of representation for the dummy to be included, but recent empirical findings have shown that the model is insensitive to the choice of dummy representation. The effects of sudden influential events on the development of a time series, can be evaluated by adding intervention (pulse) variables to the model. Incorporation of intervention variables has a number of effects that include; level shift, slope shift and pulse. Level shift is where time series level changes suddenly at the time point where the intervention took place. Slope shift is where the slope exhibits significant and permanent change after the intervention, while pulse is when the level value changes suddenly at the point of intervention and then immediately returns to its usual value before the occurrence of an influential event.

From Table 8, we report results of the trivariate DCC-MGARCH model under three distributional assumptions: Gaussian, Student's-t and skew-Student's-t with corresponding results given in Columns 2 to 10 respectively. We estimate the model with a Gaussian density in order to compare with other more complicated models such as the non-skewed-t and skewed-t. We fit a non-skewed-t density model with the ξ pegged to 1.0, although the ν is estimated, the $\log \xi$ is set to zero. For the skewed-t density model, the ν and the $\log \xi$ are all estimated. Engle (2011) states that a distribution is symmetric if an x% decline is just as likely as an x% increase for any x% change and defines skewness as a systematic deviation from symmetry with negative skewness indicating that large declines are more likely than similar sized increases. However, of note is that the β's in Table 8 correspond to the mean parameters while the g's correspond to the GARCH parameters. On close inspection of Table 8, the move from Gaussian to Student's-t, with the ν's hovering around 7 indicates that the tails are quite fat. The two parameters governing the DCC recursion are DCC(α) and DCC(β). The ν and the log-likelihood improvement achieved by the DCC-MGARCH with t distribution show strong evidence against the Gaussian DCC-MGARCH model.

The parameters governing the dynamics of correlations in Table 8 are all significant for all models and the persistence parameters for the volatilities are all high > 0.9 with all stationarity conditions being satisfied. Changing the DCC specification to a DCC-MGARCH with skew-t model yields several effects.(1) the log-likelihood value increased substantially by the addition of four parameters,(2) the ν parameter also increased in all stock market return series combinations. The main reason for the increase in the log-likelihood is probably due to the effects of tails and skewed distribution on the volatility and correlation dynamics of the time series. The skewness parameters of the DCC-MGARCH with t density are mostly significant with the exception of $\log \xi_2$ for DMs model and $\log \xi_3$ for the combined markets model. Furthermore, the signs of the skewness coefficients in Table 8 are in line with the summary statistics in Table 1. All the model selection criteria (AIC and SBC) are more favourable for the DCC-MGARCH with skew-t specification than with other models.

Thus, the results reveal that the trivariate GARCH model with skew-Student's-t distribution for the innovation improves the models' quality compared with models with Gaussian and Student's-t distributions as well as providing a better fit to the returns data. Studies such as Giot and Laurent (2003) have shown the superiority of the univariate skew-Student's-t density over the Gaussian and Student's t densities when forecasting the 1-day-ahead VaR of many assets for long and short trading positions (i.e. both in-sample and out-of-sample). Bauwens and Laurent (2005) highlight the use of the multivariate skew-Student's-t density using a VaR application on several portfolio of assets and exchange rates and shows that in several cases this density improves the quality of out-of-sample VaR forecast in comparison with a symmetric model, and that in no case is the performance deteriorated. The likelihood ratio (LR) test favours the skew-Student's-t density model. Indeed all the 3 developed market returns are negatively skewed. The LR test of significance of skewness calculated by $\log \chi^2(3) = 27.8301$ and is significant. For EMs, the LR test of significance of skewness $\log \chi^2(3) = 27.8259$ and are all highly significant. For combined markets, the LR test of significance of skewness $\log \chi^2(3) = 30.8915$ and is also significant.

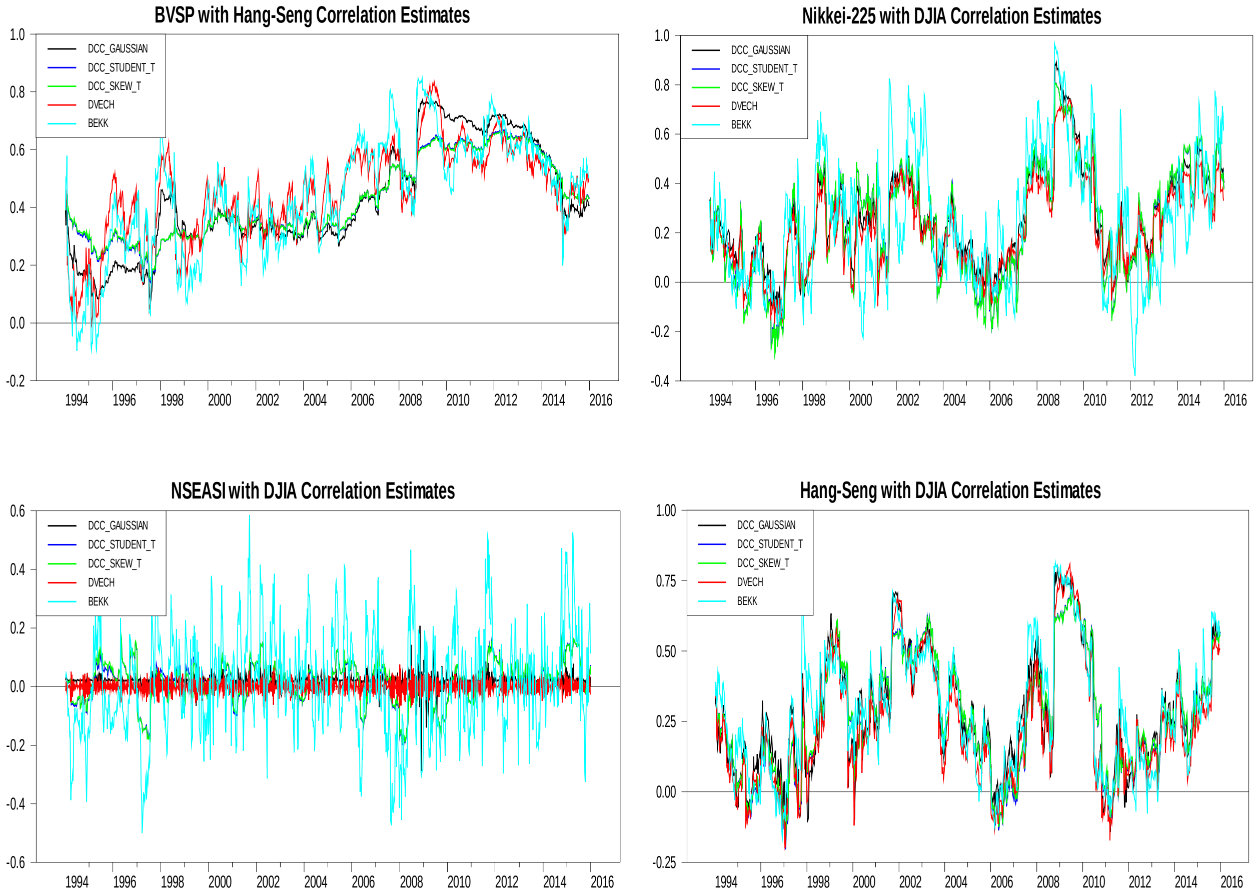
Figures 3 & 4 present a comparison of correlation estimates for fitted DVECH, BEKK and DCC-MGARCH models respectively. The correlation estimates were computed using the volatilities in Figure A. For the BVSP–Hang-Seng correlation estimates, the correlations were between 0.2 and 0.8 from 2000 to 2016. There was a notable increase in correlation among these 2 EMs during the GFC and consistent decline afterwards. Additionally, this provides an interesting scenario whereby we can observe the BVSP–Hang-Seng correlation experiencing an

Table 8: DCC with Gaussian, Student's t & Skew-Student's t Residual Estimates

	Emerging Stock Markets			**Developed Stock Markets**			**Combined Stock Markets**		
Parameter	Normal	Std's -t	Skew-t	Normal	Std's -t	Skew-t	Normal	Std's -t	Skew-t
$\beta_{1,1}$	0.1562**	0.1416**	0.1983**	0.1626**	0.1920**	0.1362**	0.1617**	0.1486**	0.2032**
	(0.0516)	(0.0415)	(0.0450)	(0.0559)	(0.0515)	(0.0517)	(0.0481)	(0.0376)	(0.0351)
$\beta_{1,2}$	0.2924**	0.3291**	0.3164**	-0.1001**	-0.0979**	-0.1035**	0.2925**	0.3298**	0.3168**
	(0.0350)	(0.0315)	(0.0311)	(0.0221)	(0.0248)	(0.0221)	(0.0345)	(0.0314)	(0.0268)
$\beta_{2,1}$	0.2983**	0.3468**	0.2352*	0.1434	0.1509	0.1020	0.2418**	0.2710**	0.2119**
	(0.1065)	(0.1073)	(0.1059)	(0.0794)	(0.0779)	(0.0751)	(0.0578)	(0.0532)	0.0491
$\beta_{3,1}$	0.2114**	0.2370**	0.1701*	0.2425**	0.2638**	0.2154**	0.2229**	0.2187**	0.1859*
	(0.0810)	(0.0795)	(0.0782)	(0.0521)	(0.0520)	(0.0490)	(0.0855)	(0.0729)	0.0723
$g_{1,1}$	0.1907**	0.0354	0.0396*	0.1887**	0.1387**	0.1459	0.1977**	0.0436*	0.0458**
	0.0417	(0.0181)	(0.0168)	(0.0584)	(0.0485)	(0.0430)	(0.0420)	(0.0196)	(0.0098)
$g_{1,2}$	0.3815**	0.3791**	0.3698*	0.0966**	0.0696**	0.0749**	0.3916**	0.3987**	0.3881**
	(0.0443)	(0.0476)	(0.0437)	(0.0159)	(0.0137)	(0.0131)	(0.0466)	(0.0516)	(0.0175)
$g_{1,3}$	0.6879**	0.7148**	0.7154**	0.8709**	0.9031**	0.8967**	0.6823**	0.7037**	0.7051**
	(0.0257)	(0.0248)	(0.0238)	(0.0229)	(0.0189)	(0.0174)	(0.0269)	(0.0266)	(0.0084)
$g_{2,1}$	0.7376**	0.6598**	0.5592**	1.0248**	0.4013*	0.3886**	0.4609**	0.3053*	0.2715**
	(0.2108)	(0.2264)	(0.1715)	(0.3535)	(0.1862)	(0.1482)	(0.1336)	(0.1250)	0.0290**
$g_{2,2}$	0.1157**	0.0984**	0.1030*	0.1075**	0.0665**	0.0644**	0.1892**	0.1201**	0.1221**
	(0.0194)	(0.0202)	(0.0174)	(0.0256)	(0.0201)	(0.0166)	(0.0316)	(0.0334)	(0.0084)
$g_{2,3}$	0.8484**	0.8733**	0.8755**	0.7870**	0.8926**	0.8946**	0.7334**	0.8283**	0.8322**
	(0.0236)	(0.0248)	(0.0182)	(0.0567)	(0.0344)	(0.0263)	(0.0479)	(0.0486)	(0.0067)
$g_{3,1}$	0.1318*	0.1369**	0.1299**	0.2172*	0.1861**	0.1825**	0.1472**	0.1817**	0.1709**
	(0.0533)	(0.0526)	(0.0432)	(0.0845)	(0.0678)	(0.0597)	(0.0546)	(0.0517)	(0.0309)
$g_{3,2}$	0.0736**	0.0622**	0.0613**	0.1128**	0.0871**	0.0887**	0.0791**	0.0686**	0.0679**
	(0.0138)	(0.0123)	(0.0085)	(0.0244)	(0.0198)	(0.0176)	(0.0152)	(0.0078)	(0.0043)
$g_{3,3}$	0.9163**	0.9296**	0.9303**	0.8469**	0.8747**	0.8729**	0.9081**	0.9187**	0.9192**
	(0.0146)	(0.0127)	(0.0087)	(0.0374)	(0.0289)	(0.0258)	(0.0161)	(0.0061)	(0.0037)
DCC(α)	0.0116**	0.0100**	0.0097**	0.0436**	0.0429**	0.0432**	0.0255**	0.0237**	0.0232**
	(0.0024)	(0.0024)	(0.0022)	(0.0053)	(0.0061)	(0.0059)	(0.0053)	(0.0052)	(0.0034)
DCC(β)	0.9877**	0.9888**	0.9890**	0.9403**	0.9430**	0.9433**	0.9559**	0.9627**	0.9637**
	(0.0027)	(0.0029)	(0.0026)	(0.0079)	(0.0086)	(0.0083)	(0.0097)	(0.0090)	(0.0060)
ν	–	7.3722	7.7064**	–	7.8669**	8.3643**	–	7.4254**	7.8677**
		(0.7739)	(0.7597)	–	(0.6971)	(0.8436)	–	(0.8245)	(0.6670)
$\log \xi_1$	–	–	0.1060**	–	–	-0.1945**	–	–	0.1033**
	–	–	(0.0369)	–	–	(0.0423)	–	–	(0.0323)
$\log \xi_2$	–	–	-0.1739**	–	–	-0.0449	–	–	-0.2012**
	–	–	(0.0396)	–	–	(0.0395)	–	–	(0.0424)
$\log \xi_3$	–	–	-0.0982*	–	–	-0.1029**	–	–	-0.0604
	–	–	(0.0411)	–	–	(0.0398)	–	–	0.0405
Log Lik.	-8580.77	-8480.38	-8466.47	-7507.07	-7406.23	-7392.31	-7860.39	-7759.67	-7744.22
AIC	14.988	14.815	14.796	13.116	12.942	12.923	13.732	13.558	13.537
SBC	15.054	14.885	14.879	13.182	13.012	13.007	13.798	13.629	13.620
LR(Skew)	27.8259			27.8301			30.8915		
	(0.0000)			(0.0000)			(0.0000)		

Note: Numbers in parentheses indicate the standard errors. Superscripts **,* indicates significance at 1% and 5% levels. Log Lik., LR, AIC and SBC stand for Log likelihood, likelihood ratio, Akaike and Schwarz information criteria. The $i = 1, 2, 3$ refer to NSEASI, BVSP and Hang-Seng indices (emerging markets) and the same numbers for developed markets represent FTSE-100, Nikkei-225 and DJIA indices. For the combined markets, $i = 1, 2, 3$ denote NSEASI, DJIA and Hang Seng indices respectively. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

Figure 3: Correlation Estimates Comparison (DVECH, BEKK & DCC Models)

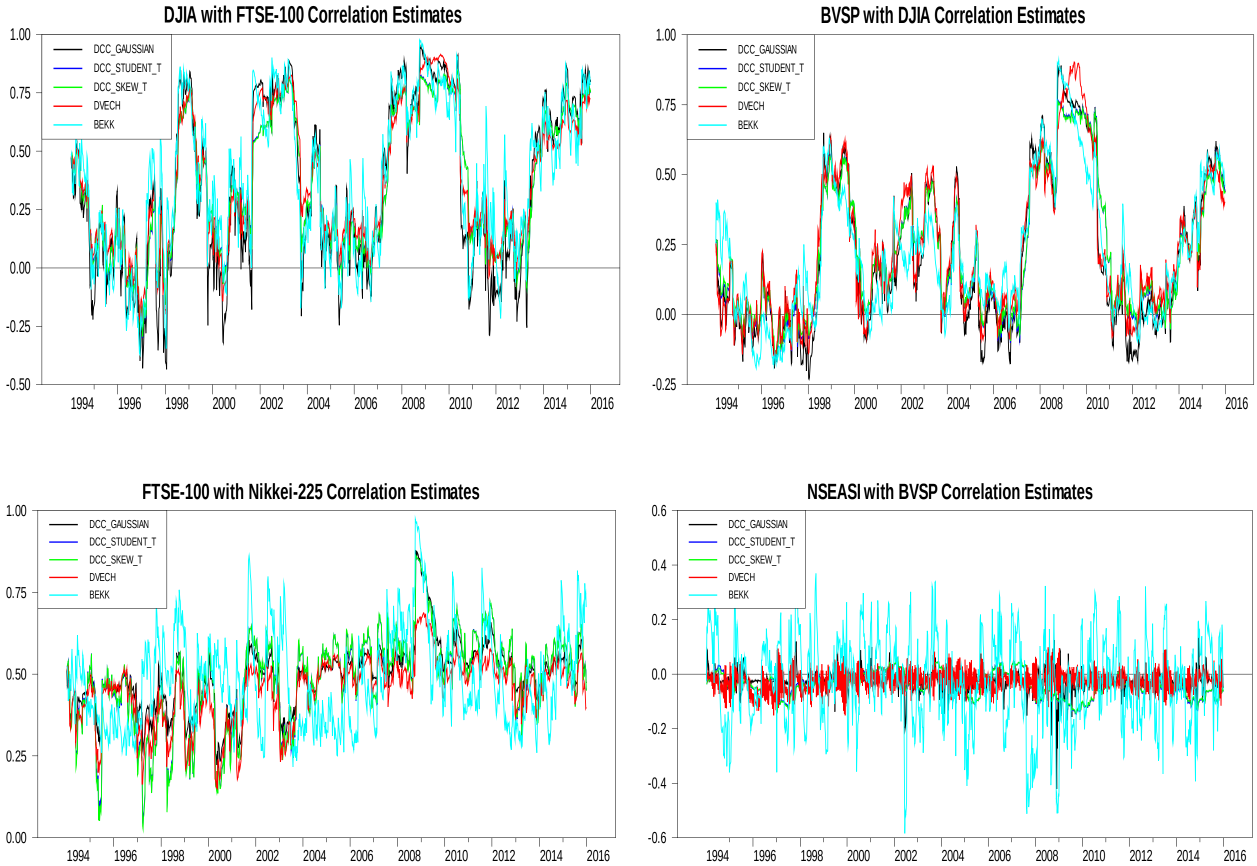


upward trend. It shows strong empirical evidence that the correlations are time varying. The Nikkei–DJIA correlation is even higher particularly during major financial crises. This empirical evidence has vital implications for equity portfolio diversification among markets as the increasing and time-varying correlation implies that the two markets (BVSP and Hang-Seng) are becoming increasingly integrated which suggests the possibility of reduced benefits due to international portfolio diversification even among EMs.

In terms of comparison of correlation estimates between the three models (DVECH, BEKK and DCC), the BEKK-MGARCH model correlation estimates tend to be higher than the corresponding correlation estimates of DVECH and DCC models (i.e. it exhibits larger variability). The NSEASI–DJIA correlation estimates are quite low in comparison with correlation among other markets. The DJIA–FTSE-100 correlation estimates are the highest among all the markets considered with the estimates very close to 1 around 1999, 2002–2003 and 2008–2010 which coincides with periods of economic recessions and large fluctuations in financial markets. For the BVSP–DJIA correlations, there were four noticeable declines (i.e. 1994–1998, 2000–2001, 2005–2007 and 2011–2014). The most significant increase is in the period 2008–2010. It suffice to state that volatility and correlation are two major constituents of covariance while correlation is standardised covariance.

Engle's (2001) DCC-MGARCH model is a considerable improvement over the DVECH and BEKK specifications and allows for time-varying correlations. Earlier, Tse and Tsui (1998) proposed a DCC-MGARCH model, but no attempt was made to allow for seperate estimation of the univariate GARCH equations and DCC estimator. The DCC-MGARCH model is capable of capturing the volatility correlations between markets or assets either directly through

Figure 4: Correlation Estimates Comparison (DVECH, BEKK & DCC Models)



its conditional variance or indirectly through its conditional covariances as well as the ability to uncover volatility spillover from one market or asset to another. The model also generates fewer parameters compared to other MGARCH models and overcome some of their weaknesses. Additionally, the model possesses the flexibility of univariate GARCH models with its two-step estimation procedure. Because economic activities change over time, the dynamic model becomes practically more attractive. We analyse the DCC-MGARCH model of stock market return pairs in order to uncover the correlation structure between the stock markets over the sample period. Engle and Shephard (2001) note that the DCC evolution process is a nonlinear process and equally presents a natural method to examine the relationship between volatility and correlation. Frank and Hesse (2009) note that given the high volatility during financial crises, the assumption of CCC is often not quite realistic especially in times of stress where correlations can change rapidly. They recommend the DCC-MGARCH model as a better choice since correlations are time varying. In addition, Zhou and Nicholson (2015) assess the economic value of modelling covariance asymmetry (i.e. when conditional volatility and correlation of returns rise more after negative return shocks than after positive shocks of the same size) for financial assets. They investigate whether investors could gain significant economic benefits from incorporating the feature into mixed-asset portfolio diversification. They find that covariance asymmetry is a value-added feature for mixed-asset diversifications.

4.4 Implications of Estimation Results

In this subsection, we examine the economic and financial implications of the results from the fitted MGARCH models considered in the paper. A major finding in line with extant studies such as Ozer-Imer and Ozkan (2014) among others, is that variances tend to increase during significant global market events such as the GFC and that correlations among EMs are lower compared with correlations among DMs in the sample period. This implies that there is less potential for diversification among DMs and that EMs can offer portfolio diversification opportunities both among EMs and for advanced market investors. In addition, the GFC of 2008–2009 impacted more on DMs than on EMs. The paper also find that the correlation estimates from the fitted BEKK-MGARCH models are often higher than the estimates from DVECH and DCC (including all the estimated variants) models. Additionally, the BEKK-MGARCH model (see Table A2, in Appendices) often exaggerate volatility persistence in stock markets compared with the BEKK-AMGARCH class model. The BEKK-MGARCH specification by construction assumes symmetric effects between positive and negative shocks. This result is consistent with the findings of Salisu and Oloko (2015). However, The CCC-VARMA-AMGARCH model did not detect substantial presence of asymmetric behaviour in emerging markets which is also in line with findings from recent studies.

Comparing the magnitude of estimates of the combined markets in BEKK-MGARCH model (Table A2, Column 6), the shock of an emerging market (NSEASI) has the largest effect (0.6121), followed by another emerging market (Hang-Seng) (0.2475) on their own variance, with a developed market (DJIA) having the smallest own shock effect (0.2085). This suggests that past shocks play more crucial role in the volatility of EMs than those in the volatility of the DMs. This according to Li and Giles (2015) can be explained by the fact that the more advanced a market is, the less affected it is by its own past shocks. It can also imply that the EMs exhibit less market efficiency than the DMs as the effects of the shock takes a longer time to dissipate. This finding can help guide investors in their investment decisions. We also find that the dummy variable coefficients for the GFC in the variance and covariance equations are all insignificant for the three EMs (see, Table A3, Columns 2 & 3) with the exception of $D_{GFC(1,1)}$ which is significant at 1% level. This suggests that the GFC did not influence cross-market volatility among EMs, but had slight influence on own-volatility, as in the case of $D_{GFC(1,1)}$ which is positive. For DMs (see, Table A3, Columns 4 & 5) some of the dummy variable coefficients for the GFC in the variance and covariance equations are significant except for $D_{GFC(2,2)}$, $D_{GFC(3,2)}$ and $D_{GFC(3,3)}$ (From Column 5). This implies that the GFC influenced cross-market volatility among DMs more than own-volatility, providing justification for the existence of spillover effect during the GFC.

Results further reveal that the trivariate-MGARCH model with skew-Student's-t distribution for the innovation improves the models' quality compared with models with Gaussian and Student's-t distributions and provides a better fit to the returns data which is partly due to its taking into account the skewed feature of the returns. We equally find that based on all the estimated models, their performance can be improved by avoiding/relaxing the normality assumption. The paper recommends that in modelling stock market volatility dynamics and spillovers; skewness, asymmetry and fat tails when they exist should be taken into account in the modelling process. Overall, the above empirical evidences have strong implications for equity portfolio diversification among markets as the increasing and time-varying correlation implies that emerging markets are becoming increasingly integrated which suggests the possibility of reduced benefits due to international portfolio diversification even among EMs.

5 Concluding Remarks

In this paper, we investigate stock markets volatility spillovers in selected emerging and developed markets using several MGARCH model variants. To determine the stationarity of the returns data employed, we conduct unit root tests (with and without structural breaks) and establish the existence of stationarity of the returns. Furthermore, we employ Inclan and

Tiao's variance breaks detection test and uncover significant evidence of structural breaks in the unconditional variance in all the market returns. The comparison of MGARCH models carried out for the selected markets is to enable analysis of their dynamic interactions and spillover effects in different stock markets which is of considerable interest to investors with a portfolio of assets especially during financial crises. This paper primarily focuses on modelling of volatility spillovers and interdependence among EM and DM returns by comparing and contrasting several MGARCH models of volatility. Apart from using the conventional modelling strategies, we consider a class of flexible multivariate densities that can model both skewness and heavy tails in the distribution of the errors. It has been shown by many recent studies that ignoring the skewed feature of returns in the modelling process could lead to overestimation (or underestimation) of risk and could consequently lead to wrong decisions on portfolio or hedging strategies.

Major findings reveal that correlations among EMs tend to be lower compared with correlations among DMs suggesting greater degree of interaction between DMs than among EMs. Thus, the hypothesis that stock market correlation is higher during periods of excessive volatility in markets (and tends to have strengthening effect on stock market linkages) is now established and has been further validated from our findings. Consistent with extant literature, the conditional volatility of each stock market due to its previous short and long-run shocks are to a large extent higher than cross-volatility shocks particularly for EMs with similar trend for DMs. In addition, we find that both the correlations and the unconditional covariance matrix of stock returns are time varying. This implies that when time variation is neglected, the persistence of conditional variance and correlations tends to be high. We also find that past shocks play more crucial role in the volatility of EMs than those in the volatility of DMs. This implies that the more advanced a market is, the less affected it is by its own past shocks. It can also suggest that the EMs are less efficienct than the DMs as the effects of the shock takes a longer time to dissipate. This finding has significant financial implications and can help guide investors in their investment decisions. We also find that the GFC did not significantly influence cross-market volatility among EMs, but had slight influence on own-volatility. For DMs some of the dummy variable coefficients for the GFC in the variance and covariance equations are significant suggesting that the GFC influence cross-market volatility among DMs more than own-volatility, justifying the existence of spillover effect during the recent GFC.

In terms of selecting the best MGARCH model for the analysis of volatility interactions and spillover effects in the context of recent financial crises, our paper recommends the use of the DCC-MGARCH-with-Skew-t model which is more suited than its close competitors if skewness and excess kurtosis are present in the data. Several other models have been proposed including the regime-switching DCC model, the component-DCC model, the smooth-transition CC model, the factor-spline-GARCH DCC model and the mDCC model (see, Silvennoinen and Teräsvirta, 2005 and Bauwens *et al.*, 2013). These recent extensions are due to the need for more flexibility in the modelling process. Taking into account the skewed feature of returns could lead to an important outcome in the quest for the development of effective long-term risk measure in financial markets. These results of the analysis of spillover effects between stock markets could further shed light on the impact of financial crises on stock market volatility spillover.

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Japan. All other remaining errors are our responsibility.

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Appendices

Table A1: Sudden Changes in Volatility: Breakpoints Detection Using Iterated Cumulative Sum of Squares (ICSS) Test for Emerging and Developed Stock Markets

Indices	Period	Major Events
		Emerging Stock Markets
NSEASI (Nigeria)	1995:03:27	
	1995:08:28	Nig. investment promotion Act enacted to guarantee the ease of transfer of funds
	1999:05:03	Introduction of automated trading system replacing the open outcry method.
	2008:05:05	NSE market near crash partly due to spillover effects from subprime crisis.
	2009:09:21	Global financial crisis, Banking crisis, second wave of banking reforms.
	2014:10:06	
	2015:04:06	Impact of the 2015 national general elections.
BVSP (Brazil)	1994:07:04	
	1995:04:24	
	1997:07:07	Asian financial crisis and its impact on investor confidence,
	1999:03:15	Introduced an internet-based trading system; Brazilian currency crisis
	2003:01:20	
	2008:09:15	Global financial crisis
	2009:05:25	Global financial crisis
SSECI (China)	1994:07:25	
	1994:08:01	Companies began launch of their A-share IPOs by competitive bidding through the trading system.
	1995:05:08	
	1995:05:22	Suspension of T-bond futures trading.
	1996:04:08	
	1996:11:18	The SSE changed the constituents of SSE-30 index for the first time.
	1996:12:16	Effects of SSE's imposition of a 10% daily up/down limits on trading prices of shares and funds.
	2000:05:22	Effects of the decision to allow transferred rights shares to be traded in market
	2006:12:04	
	2009:03:16	Global financial crisis
	2010:11:15	Implementation of T-bond bilateral quotations
	2014:11:17	Launch of Shanghai-Hong Kong Stock Connect on 17th November
HANG SENG (Hong Kong, China)	1995:05:08	
	1997:01:06	
	1997:09:29	Transfer of sovereignty to China, Asian currency crises
	1998:10:12	Russian crisis & Ruble devaluation; DJIA, S&P500 & NASDAQ fell by >20%
	2001:11:12	Economic effects due to 9/11 attacks.
	2004:06:21	Introduction of the H-shares index options.
	2007:08:06	
	2009:07:20	Global financial crisis
	2011:07:25	Implemented the T+2 finality arrangement for securities market money settlement in the central clearing and settlement system.
	2012:01:16	
	2015:03:23	Launch of short-selling of eligible Shanghai-listed A shares under Shanghai-Hong Kong Stock Connect.

Indices	**Period**	**Major Events**
		Developed Stock Markets
	1997:10:20	Asian financial crisis
	2002:12:09	
NIKKEI-225	**2008:08:18**	Lehman shock, Global financial crisis, economic recession.
(Japan)	**2008:10:27**	GFC; Appreciation of the yen; Nikkei hitting its lowest point since the bubble.
	2009:11:30	
	1997:03:17	
	2001:03:12	The Dow plunges sharply prompted by econ. slowdown & losses in tech. mrkts
	2001:09:24	Impact of September 11th attack caused global stock markets to drop sharply,
	2002:07:01	Enron & WorldCom accounting scandals shaking investor confidence
DJIA	2003:03:24	
(USA)	2007:02:12	The impact of the initial signs of the sub-prime mortgage crisis
	2009:03:23	Global financial crisis; the Dow fell to its lowest level since 1997.
	2010:08:02	
	2011:06:13	
	2011:12:12	
	2014:09:29	
	1997:07:14	
	2001:07:30	dot-com (technology) bubble aftermath
	2003:06:02	
DAX-30	**2008:09:22**	Sub-prime mortgage crisis aftermath; Global financial crisis
(Germany)	**2009:03:09**	Global financial crisis
	2010:07:05	S&P downgrades Greece's sovereign credit rating to junk
	2011:07:25	Stock markets globally plummet and remain volatile till year-end.
	2011:12:19	
	2014:09:15	
	1994:11:21	
	1997:08:25	
	2003:03:31	
	2006:05:01	
FTSE-100	**2008:08:25**	Global financial crisis
(UK)	**2009:03:09**	Global financial crisis
	2010:07:05	S&P's downgrade of Greece's sovereign credit rating to junk
	2011:06:20	
	2011:11:28	
	2014:12:01	

Note: The identified break points are all significant at the 5% level. Dates in boldface indicate break points that occur during the Global financial crisis (GFC) period.

Table A2: BEKK-MGARCH Estimates (Emerging & Developed Stock Markets)

	Emerging Markets		Developed Markets		Combined Markets	
Parameter	BEKK–MGARCH	BEKK–AMGARCH	BEKK–MGARCH	BEKK–AMGARCH	BEKK–MGARCH	BEKK–AMGARCH
Constant	0.1491	0.1410**	0.2408**	0.1230*	0.1694**	0.1562**
	(0.0786)	(0.0477)	(0.0561)	(0.0484)	(0.0507)	(0.0472)
r_{t-1}	0.2925**	0.3029**	-0.1582**	-0.1325**	0.2999**	0.2989
	(0.0397)	(0.0337)	(0.0265)	(0.0235)	(0.0385)	(0.0322)
Constant	0.2278*	0.1629	0.1322	0.0408	0.2453**	0.1893**
	(0.1091)	(0.1043)	(0.0850)	(0.0759)	(0.0649)	(0.0541)
r_{t-1}	-0.0888**	-0.0842**	-0.0493	-0.0216	-0.1190**	-0.1223**
	(0.0268)	(0.0239)	(0.0275)	(0.0266)	(0.0234)	(0.0271)
Constant	0.1915	0.1299	0.3008**	0.2570**	0.2533*	0.1551*
	(0.0930)	(0.0771)	(0.0579)	(0.0491)	(0.0963)	(0.0774)
r_{t-1}	-0.0378	-0.0243	-0.1549**	-0.1101**	-0.0178	-0.0083
	(0.0261)	(0.0227)	(0.0281)	(0.0258)	(0.0265)	(0.0259)
$c_{1,1}$	0.4364**	0.4192**	0.4076**	0.3898**	0.4745**	0.4454**
	(0.1177)	(0.0534)	(0.0657)	(0.0625)	(0.1530)	(0.0447)
$c_{2,1}$	0.0236	-0.0604	0.2298	0.9811**	-0.0858	-0.0536
	(0.1103)	(0.1215)	(0.1469)	(0.1431)	(0.1740)	(0.0809)
$c_{2,2}$	0.6363**	0.5456**	-0.1302	-0.0244	0.2851*	0.5860**
	(0.1091)	(0.0895)	(0.1293)	(0.2674)	(0.1306)	(0.0633)
$c_{3,1}$	0.0504	-0.0017	0.1588	0.0311	0.0160	0.0848
	(0.0803)	(0.0942)	(0.0931)	(0.0963)	(0.0850)	(0.0901)
$c_{3,2}$	0.3476**	0.3533**	-0.2186	0.4233	0.1330	-0.0061
	(0.0932)	(0.0891)	(0.2076)	(0.4901)	(0.1015)	(0.0820)
$c_{3,3}$	0.2247**	0.2649**	-0.2032*	0.1203	0.2733**	0.0000
	(0.0464)	(0.0689)	(0.1003)	(1.6087)	(0.0797)	(0.3439)
$\alpha_{1,1}$	0.6363**	0.6157**	0.3651**	-0.0043	0.6121**	0.6107**
	(0.0572)	(0.0355)	(0.0401)	(0.0422)	(0.0591)	(0.0352)
$\alpha_{1,2}$	-0.0059	0.0249	0.2727**	-0.1003	0.0341	0.0343
	(0.0454)	(0.0349)	(0.0627)	(0.0812)	(0.0306)	(0.0205)
$\alpha_{1,3}$	0.0380	0.0789**	0.1592**	-0.3590**	0.0505	0.0823**
	(0.0407)	(0.0268)	(0.0422)	(0.0398)	(0.0392)	(0.0292)
$\alpha_{2,1}$	0.0132*	0.0128	0.0279	0.0132	0.0167	0.0276
	(0.0059)	(0.0065)	(0.0277)	(0.0245)	(0.0398)	(0.0285)
$\alpha_{2,2}$	0.2069**	0.1896**	-0.0002	0.0877	0.2085**	-0.0368
	(0.0289)	(0.0222)	(0.0544)	(0.0518)	(0.0621)	(0.0394)
$\alpha_{2,3}$	-0.0085	-0.0317	-0.0082	-0.0142	0.0087	-0.1708**
	(0.0248)	(0.0178)	(0.0244)	(0.0222)	(0.0524)	(0.0414)
$\alpha_{3,1}$	-0.0093	-0.0151	0.0109	-0.3324**	-0.0055	-0.0021
	(0.0130)	(0.0128)	(0.0718)	(0.0371)	(0.0087)	(0.0126)
$\alpha_{3,2}$	0.0515	-0.1755**	0.1604*	-0.2552**	0.0647*	-0.0846**
	(0.0600)	(0.0403)	(0.0668)	(0.0653)	(0.0314)	(0.0244)
$\alpha_{3,3}$	0.2338**	0.0257	0.2967**	0.1031*	0.2475**	0.0943*
	(0.0400)	(0.0411)	(0.0310)	(0.0411)	(0.0292)	(0.0386)
$\beta_{1,1}$	0.8271**	0.8340**	0.9173**	0.9208**	0.8326**	0.8305**
	(0.0278)	(0.0154)	(0.0135)	(0.0174)	(0.0325)	(0.0154)
$\beta_{1,2}$	0.0033	-0.0092	-0.0439**	-0.0478	-0.0133	-0.0123
	(0.0178)	(0.0147)	(0.0102)	(0.0435)	(0.0153)	(0.0109)

$\beta_{1,3}$	-0.0139	-0.0304	-0.0456**	0.0084	-0.0207	-0.0339*
	(0.0178)	(0.0125)	(0.0111)	(0.0175)	(0.0201)	(0.0136)
$\beta_{2,1}$	-0.0045*	-0.0031	-0.0021	-0.0592**	0.0052	0.0119
	(0.0018)	(0.0027)	(0.0066)	(0.0144)	(0.0271)	(0.0147)
$\beta_{2,2}$	0.9695**	0.9666**	0.9911**	0.8915**	0.9657**	0.8690**
	(0.0065)	(0.0064)	(0.0025)	(0.0301)	(0.0209)	(0.0201)
$\beta_{2,3}$	-0.0003	0.0029	0.0032	-0.0019	-0.0064	-0.0457*
	(0.0057)	(0.0059)	(0.0021)	(0.0188)	(0.0184)	(0.0180)
$\beta_{3,1}$	0.0012	0.0037	-0.0048	0.0091	-0.0015	-0.0031
	(0.0039)	(0.0046)	(0.0273)	(0.0198)	(0.0039)	(0.0051)
$\beta_{3,2}$	-0.0196	-0.0276**	-0.0660**	-0.0011	-0.0124	0.0051
	(0.0154)	(0.0098)	(0.0213)	(0.0425)	(0.0089)	(0.0080)
$\beta_{3,3}$	0.9659**	0.9545**	0.9362**	0.8635**	0.9666**	0.9676**
	(0.0099)	(0.0074)	(0.0140)	(0.0191)	(0.0076)	(0.0059)
$\gamma_{1,1}$	–	-0.0167	–	-0.2663**	–	-0.0186
		(0.1088)		(0.0686)		(0.0729)
$\gamma_{1,2}$	–	-0.0158	–	-0.0026	–	-0.0821**
		(0.0529)		(0.1091)		(0.0306)
$\gamma_{1,3}$	–	0.0210	–	-0.2467**	–	-0.0359
		(0.0429)		(0.0787)		(0.0348)
$\gamma_{2,1}$	–	-0.0003	–	-0.0532	–	-0.0111
		(0.0150)		(0.0328)		(0.0369)
$\gamma_{2,2}$	–	-0.0891	–	-0.3041**	–	-0.4522
		(0.0528)		(0.0620)		(0.0462)
$\gamma_{2,3}$	–	0.0594	–	0.0727*	–	-0.0918
		(0.0384)		(0.0351)		(0.0572)
$\gamma_{3,1}$	–	-0.0027	–	-0.1238	–	0.0023
		(0.0234)		(0.0648)		(0.0192)
$\gamma_{3,2}$	–	-0.2574**	–	-0.1856*	–	-0.0669
		(0.0587)		(0.0836)		(0.0342)
$\gamma_{3,3}$	–	-0.3946**	–	-0.3058**	–	-0.3106**
		(0.0399)		(0.0606)		(0.0359)
Log-likelihood	-8607.514	-8561.906	-7462.039	-7366.101	-7878.433	-7798.384
AIC	15.0610	14.9970	13.0640	12.9120	13.7900	13.6660
SBC	15.1930	15.1690	13.1960	13.0840	13.9220	13.8370

Note: Numbers in parentheses indicate the standard errors. Superscripts **,* indicate significance at 1% and 5% levels. AIC and SBC stand for Akaike and Schwarz information criteria. The $i = 1, 2, 3$ refer to NSEASI, BVSP and Hang-Seng indices (emerging markets) and $i = 1, 2, 3$ for developed markets represent FTSE-100, Nikkei-225 and DJIA indices respectively. For the combined markets, $i = 1, 2, 3$ denote NSEASI, DJIA and Hang Seng indices respectively. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

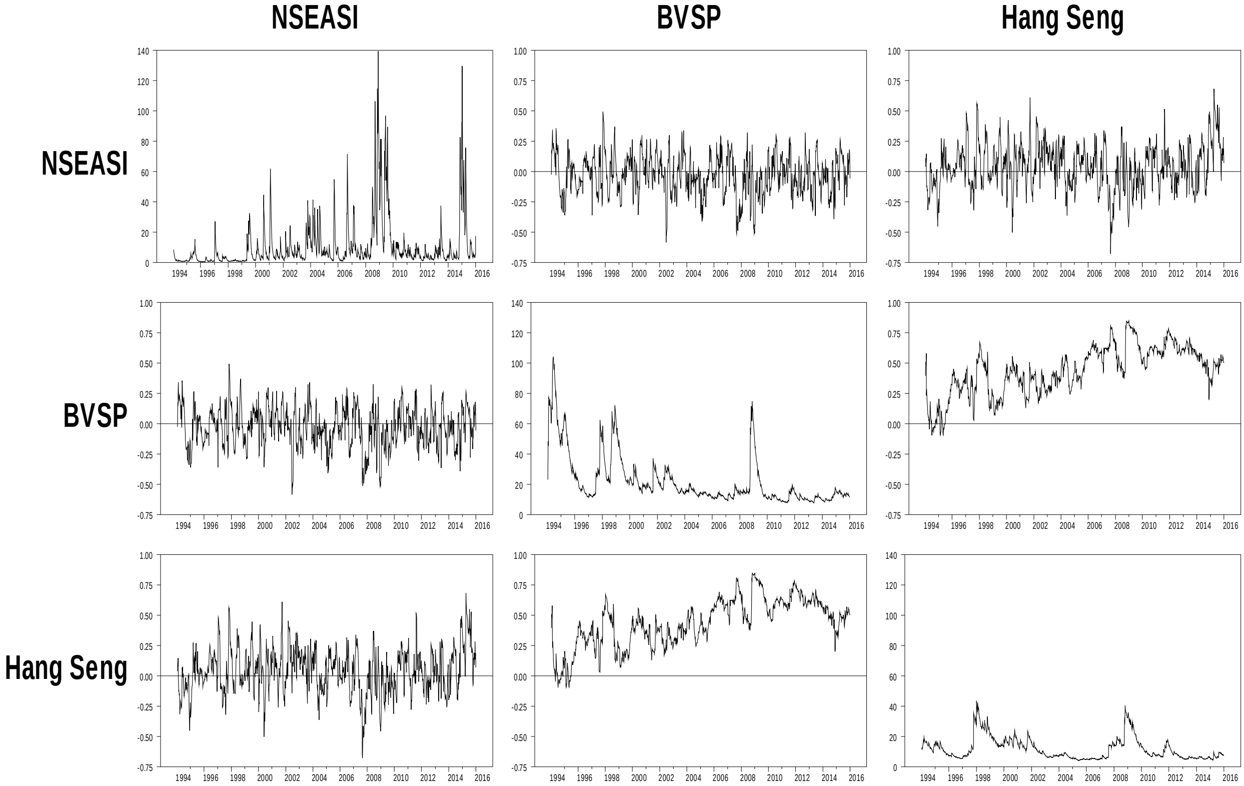
Table A3: BEKK-MGARCH Estimates (With Financial Crisis Period Dummies)

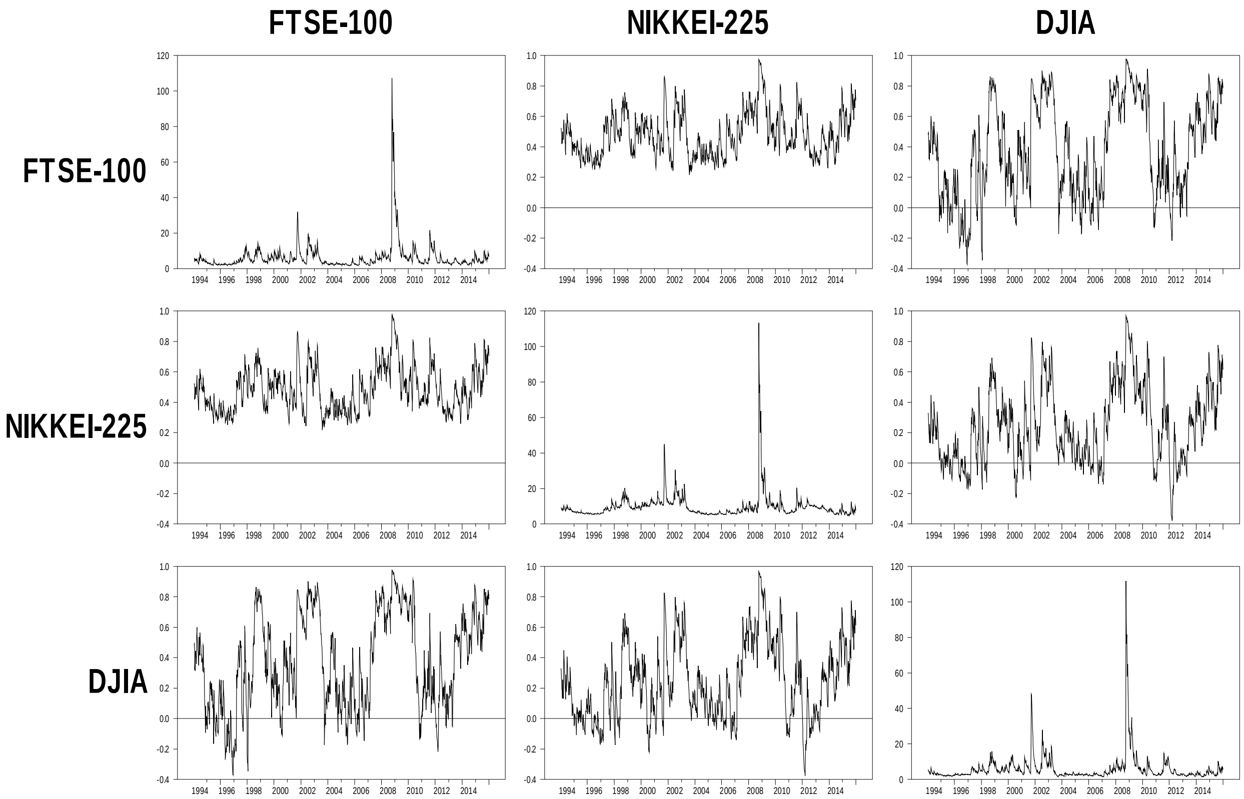
	Emerging Stock Markets		Developed Stock Markets		Combined Stock Markets	
Parameter	BEKK–MGARCH	BEKK–AMGARCH	BEKK–MGARCH	BEKK–AMGARCH	BEKK–MGARCH	BEKK–AMGARCH
Constant	0.1482**	0.1348**	0.2358**	0.1809*	0.1206**	0.1509**
	(0.0371)	(0.0324)	(0.0482)	(0.0454)	(0.0384)	(0.0358)
r_{t-1}	0.3232**	0.3353**	-0.1363**	-0.1446**	0.3495*	0.3358**
	(0.0272)	(0.0323)	(0.0231)	(0.0227)	(0.0309)	(0.0346)
Constant	0.3394**	0.3020**	0.1598*	0.1065	0.2741**	0.2615**
	(0.0978)	(0.0988)	(0.0721)	(0.0719)	(0.0563)	(0.0577)
r_{t-1}	-0.1165**	-0.1068**	-0.0342	-0.0169	-0.1227**	-0.1245**
	(0.0259)	(0.0237)	(0.0244)	(0.0245)	(0.0265)	(0.0263)
Constant	0.2328**	0.1955**	0.3111**	0.2849**	0.1840*	0.1820**
	(0.0753)	(0.0746)	(0.0487)	(0.0494)	(0.0824)	(0.0836)
r_{t-1}	-0.0450*	-0.0262	-0.1391**	-0.1288**	0.0072	-0.0068
	(0.0225)	(0.0238)	(0.0256)	(0.0251)	(0.0263)	(0.0262)
$c_{1,1}$	-0.2425**	0.2238**	0.3583**	0.4146**	0.2605**	0.2467**
	(0.0504)	(0.0473)	(0.0560)	(0.0741)	(0.0509)	(0.0457)
$c_{2,1}$	-0.0894	-0.0602	0.1485	0.8628**	-0.1510	-0.0759
	(0.2399)	(0.2095)	(0.0997)	(0.2787)	(0.2108)	(0.1838)
$c_{2,2}$	0.4847**	0.5869**	-0.0022	0.2447	0.3996**	0.6272**
	(0.1086)	(0.0985)	(0.1623)	(0.5620)	(0.0935)	(0.0826)
$c_{3,1}$	-0.0311	-0.1106	0.0509	0.1521	-0.0931	-0.0648
	(0.1900)	(0.1696)	(0.0915)	(0.0977)	(0.3283)	(0.1757)
$c_{3,2}$	0.2073*	0.3434*	0.0199	-0.0703	0.0439	0.0117
	(0.0983)	(0.1048)	(0.0489)	(0.3793)	(0.1148)	(0.1099)
$c_{3,3}$	0.2466	0.2966**	0.3136**	0.4237**	0.0000	0.2472
	(0.0591)	(0.0822)	(0.0509)	(0.0793)	(0.3741)	(0.1991)
$\alpha_{1,1}$	0.6504**	0.6236**	0.3156**	0.0422	0.6321**	0.6267**
	(0.0391)	(0.0378)	(0.0314)	(0.0459)	(0.0412)	(0.0379)
$\alpha_{1,2}$	-0.0519	-0.0100	0.1969**	0.1090	0.0505*	0.0349
	(0.0391)	(0.0358)	(0.0391)	(0.0605)	(0.0239)	(0.0233)
$\alpha_{1,3}$	0.0071	0.0479	0.0350	-0.2928**	0.0473	0.0437
	(0.0302)	(0.0301)	(0.0374)	(0.0444)	(0.0318)	(0.0319)
$\alpha_{2,1}$	0.0067	0.0032	0.0190	0.0130	-0.0111	0.0164
	(0.0059)	(0.0061)	(0.0205)	(0.0256)	(0.0236)	(0.0214)
$\alpha_{2,2}$	0.1840**	0.1709**	-0.0120	0.0310	-0.1242**	-0.0630
	(0.0223)	(0.0243)	(0.0300)	(0.0522)	(0.0340)	(0.0414)
$\alpha_{2,3}$	-0.0109	-0.0370	-0.0161	-0.0245	-0.2798**	-0.1638**
	(0.0172)	(0.0191)	(0.0198)	(0.0269)	(0.0371)	(0.0470)
$\alpha_{3,1}$	-0.0056	-0.0015	-0.0913*	-0.3561**	0.0072	-0.0004
	(0.0116)	(0.0114)	(0.0355)	(0.0421)	(0.0125)	(0.0124)
$\alpha_{3,2}$	-0.0011	-0.1796**	0.0397	-0.2286**	-0.1223*	-0.0723*
	(0.0327)	(0.0400)	(0.0333)	(0.0488)	(0.0210)	(0.0256)
$\alpha_{3,3}$	0.1909**	-0.0090	0.2765**	0.0784	0.0603	0.0719
	(0.0230)	(0.0392)	(0.0265)	(0.0458)	(0.0329)	(0.0445)
$\beta_{1,1}$	0.8274**	0.8360**	0.9237**	0.9115**	0.8323**	0.8295**
	(0.0159)	(0.0156)	(0.0129)	(0.0254)	(0.0172)	(0.0168)
$\beta_{1,2}$	0.0248	0.0104	-0.0287*	-0.0479	-0.0049	-0.0025
	(0.0147)	(0.0149)	(0.0135)	(0.0307)	(0.0184)	(0.0105)
$\beta_{1,3}$	0.0046	-0.0081	-0.0175	0.0014*	-0.0210	-0.0046
	(0.0124)	(0.0133)	(0.0138)	(0.0263)	(0.0483)	(0.0154)

$\beta_{2,1}$	-0.0031	-0.0023	0.0041	-0.0534**	0.0098	0.0014
	(0.0021)	(0.0021)	(0.0063)	(0.0242)	(0.0213)	(0.0184)
$\beta_{2,2}$	0.9775**	0.9704**	1.0002**	0.9052**	0.4705**	0.8727**
	(0.0046)	(0.0063)	(0.0033)	(0.0323)	(0.0963)	(0.0241)
$\beta_{2,3}$	0.0010	0.0050	0.0123	-0.0228	1.4777**	-0.0469
	(0.0039)	(0.0065)	(0.0035)	(0.0297)	(0.0571)	(0.0253)
$\beta_{3,1}$	-0.0003	0.0032	0.0341*	0.0141	-0.0034	-0.0013
	(0.0043)	(0.0039)	(0.0145)	(0.0213)	(0.0227)	(0.0049)
$\beta_{3,2}$	-0.0023	-0.0219	-0.0261*	0.0519	0.4769**	0.0043
	(0.0073)	(0.0115)	(0.0106)	(0.0269)	(0.0577)	(0.0101)
$\beta_{3,3}$	0.9780**	0.9568**	0.9498**	0.8811**	-0.4930**	0.9708**
	(0.0051)	(0.0093)	(0.0094)	(0.0197)	(0.0982)	(0.0104)
$\gamma_{1,1}$	–	0.0322	–	0.3999**	–	0.0464
		(0.1095)		(0.0699)		(0.0881)
$\gamma_{1,2}$	–	0.0281	–	0.5206	–	0.0694
		(0.0586)		(0.0775)		(0.0414)
$\gamma_{1,3}$	–	-0.0300	–	0.2426**	–	-0.0044
		(0.0460)		(0.0670)		(0.0435)
$\gamma_{2,1}$	–	0.0154	–	-0.1042*	–	0.0037
		(0.0159)		(0.0442)		(0.0371)
$\gamma_{2,2}$	–	0.1188*	–	-0.3526**	–	0.4334**
		(0.0547)		(0.0687)		(0.0567)
$\gamma_{2,3}$	–	-0.0639	–	-0.0674	–	0.0839
		(0.0406)		(0.0455)		(0.0784)
$\gamma_{3,1}$	–	-0.0185	–	0.0504	–	0.0015
		(0.0236)		(0.0779)		(0.0165)
$\gamma_{3,2}$	–	0.1748*	–	0.0618	–	0.0546
		(0.0721)		(0.0797)		(0.0428)
$\gamma_{3,3}$	–	0.3760*	–	0.3134**	–	0.2996**
		(0.0486)		(0.0584)		(0.0515)
$D_{GFC(1,1)}$	2.6638**	-2.5295**	0.2588	0.9272**	1.8057**	-2.4903**
	(0.6895)	(0.7027)	(0.2490)	(0.2865)	(0.6628)	(0.6751)
$D_{GFC(2,1)}$	-0.4830	0.8489	0.7301**	0.7195*	-0.4109	0.9085
	(0.5031)	(0.4510)	(0.2355)	(0.3348)	(0.3279)	(0.5163)
$D_{GFC(2,2)}$	-0.4126	-0.5870	0.0010	0.0049	-0.3995	-0.2646
	(1.61036)	(0.6103)	(0.4968)	(0.6241)	(0.8054)	(1.3765)
$D_{GFC(3,1)}$	-0.4642	0.7481	0.6853**	1.0362**	-0.6601	0.9594
	(0.4596)	(0.4005)	(0.2175)	(0.2885)	(0.5287)	(0.5083)
$D_{GFC(3,2)}$	-0.1074	-0.3434	-0.0213	-0.0304	-0.0439	0.3264
	(2.0919)	(0.5101)	(0.4688)	(0.3690)	(1.1068)	(1.2998)
$D_{GFC(3,3)}$	-0.2466	-0.2966	-0.3137	-0.4236	0.0000	-0.2472
	(0.9215)	(0.2929)	(0.2193)	(0.3431)	(0.8451)	(0.3822)
t shape	7.0451**	7.6374**	8.2633**	10.7538	6.8885**	8.5247**
	(0.7135)	(0.7523)	(0.8283)	(1.4973)	(0.5886)	(0.9302)
Log-likelihood	-8491.712	-8462.962	-7372.318	-7312.405	-7768.775	-7714.518
AIC	14.8710	14.8370	13.0820	12.8310	13.6110	13.5320
SBC	15.0340	15.0390	13.0820	13.0330	13.7740	13.7340

Note: Numbers in parentheses indicate the standard errors. Superscripts **,* indicate significance at 1% and 5% levels. AIC, and SBC stand for Akaike and Schwarz information criteria. The $i = 1, 2, 3$ refer to NSEASI, BVSP and Hang-Seng indices (emerging markets) and the same numbers for developed markets represent FTSE-100, Nikkei-225 and DJIA indices. For the combined markets, $i = 1, 2, 3$ denote NSEASI, DJIA and Hang Seng indices respectively. The BEKK-MGARCH model augmented with shift dummies is expressed as $\mathbf{H}_t = (\mathbf{C}^* + \mathbf{E}d_t)'(\mathbf{C}^* + \mathbf{E}d_t) + (\mathbf{A}^*)'(\varepsilon_{t-1}\varepsilon'_{t-1})\mathbf{A}^* + (\mathbf{B}^*)'\mathbf{H}_{t-1}\mathbf{B}^* + (\boldsymbol{\gamma}^*)'\mathbf{G}_{t-1}\mathbf{G}'_{t-1}\boldsymbol{\gamma}^*$,, where $\mathbf{E}$ is (like $\mathbf{C}^*$) a lower triangular matrix. Estimation methods: Broyden-Fletcher-Goldfarb-Shannon (BFGS).

Figure A: Variances (diagonal) and Correlation (off-diagonal) (Emerging and Developed Markets Return) from fitted Standard BEKK-GARCH Model (1994–2016)





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