Ekonomi och samhälle
Economics and Society

Skrifter utgivna vid Svenska handelshögskolan
Publications of the Hanken School of Economics

Nr 245

Saint Kuttu

Essays on Volatility and Time Varying Conditional Jumps in Thinly Traded African Financial Markets

Helsinki 2012

Essays on Volatility and Time Varying Conditional Jumps in Thinly Traded African Financial Markets

Key words: returns, volatility, interdependence, thin trading, equity, negative news, foreign exchange, conditional jumps, poisson process, ARJI-GARCH, emerging equity markets

Saint Kuttu
Hanken School of Economics
Department of Finance and Statistics
P.O.Box 287, 65101 Vaasa, Finland

NORDIC ENVIRONMENTAL LABEL
441 002
Printed matter

Hanken School of Economics

ISBN 978-952-232-171-8 (printed)
ISBN 978-952-232-172-5 (PDF)
ISSN-L 0424-7256
ISSN 0424-7256 (printed)
ISSN 2242-699X (PDF)

Edita Prima Ltd, Helsinki 2012

Dedicated to my Mum and the memory of my late Dad

ACKNOWLEDGMENTS

First of all, the greatest of thanks goes to God for bringing me to a successful end of my PhD education. I am profusely grateful to my supervisor, Johan Knif, for inspiring me to take the first steps toward an exciting career in financial econometrics and empirical finance, and for his numerous discussions, strong support, insightful advice, and endless encouragement.

I am also deeply grateful to Kenneth Högholm, who effortlessly provided me with administrative support and insightful comments on my research. Terje Lensberg deserves thanks for inviting me to spend the autumn of 2009 as a visiting research scholar in the Department of Finance and Management Science, Norwegian School of Economics and Business Administration.

I wish to sincerely thank Seppo Pynönnen and Björn Hansson for serving as reviewers of my dissertation, and for providing thorough and valuable comments, which significantly improved the dissertation. Thanks also goes to Tua Ericson-Knif for taking time off her busy schedule to read through the manuscript.

Special mention go to Eva Liljeblom (current Rector of Hanken and former head of Department of Finance and Statistics) and Anders Löflund (current head of Department of Finance and Statistics) for approving financial support for my PhD studies and trips abroad. The special mention also goes to Mikko Leppämäki, who through the Graduate School of Finance organised doctoral courses, which enriched my knowledge in my area of specialization. He also indefatigably organised seminars and workshops where I presented my research and got useful comments.

I wish to thank my wife, Priscilla, profusely for her unlimited patience, encouragement and support, and also for sharing the joyous and stressful moments with me throughout my PhD education. My daughter, Yayira deserves special commendation for bringing me joy and for continuing to be of immense blessings and happiness in my life. I am also grateful to Henna and her family for being the rock in Yayira's life during my PhD education. My brother Giffard deserves special thanks for his encouragement and financial support during my master's studies.

I would like to thank my colleagues at the Department of Finance and Statistics: Anand, Nadir, Hilal, David, Nasib and Olugbenga. Mates, our eagerness to discuss issues, both academic and social, and the willingness on our part to serve as a sounding board for ideas made the PhD process very interesting and enjoyable.

Finally, I wish to convey special thanks to my Mum, late Dad, and my brothers and sisters for the investments they made in me in spite of the challenges. I wish Dad were alive to see the returns from his investments. Dad, I miss you and I am eternally grateful.

Financial support from Centre for Financial Research (CEFIR), Hanken Foundation for Young Doctoral Students, Hanken Foundation, and Marcus Wallenbergs Stiftelse för Företagsekonomisk Forskning, is greatly acknowledged.

June 8, 2012

Saint Kuttu

CONTENTS

PART I:

BACKGROUND, THE ISSUE OF THIN TRADING, BRIEF OVERVIEW OF THEORY AND EMPIRICAL FINDINGS

1 INTRODUCTION

Financial markets' return and volatility, which are fundamental to asset pricing and risk management have been extensively examined in the finance literature. Perhaps the 2008-2009 global financial crisis underscores the importance of appreciating first and second moment inter-markets linkages on the part of international investors as they seek to diversify their investment portfolios into African financial markets. In particular, the new wind of democracy blowing across the African continent, which has led to greater accountability and improvement of economic management, coupled with the strengthening of institutional structures like regulatory bodies and the judiciary, have made Africa an attractive investment destination.

The 2008-2009 global financial crisis has brought to the fore the relative resilience of African economies. For instance, real gross domestic product growth for the advanced economies was 0.0%, -2.6%, 1.7% and 1.3% for 2008, 2009, 2010 and 2011 respectively. That for sub-Saharan Africa was 5.6%, 2.8%, 5.3% and 5.1% for the same period. The advanced economies are projected to grow at 1.2% during 2012, and sub-Sahara Africa is projected to grow at 5.4% during the same period[1].

Despite the increasing weight of African financial markets in the world financial market and their relevance in international portfolio diversification, studies on financial market interdependence both in the first and second moments, and time varying jumps in the second moment are focused mainly on mature markets outside the African continent (see Lin and Lee, 2010; Canarella, Miller and Pollard, 2009; Chan, 2008; Rao, 2008; Maheu and McCurdy, 2004; Mishra, 2004; Phylaktis and Ravazzolo, 2005; Chan and Maheu, 2002; Granger, Huang and Yang, 2000; and Koutmos, 1996). Accordingly, this study explores the return and volatility dynamics in African equity markets where trading is mostly non-synchronous and thin.

In particular, this thesis applies conditional heteroskedastic models to examine the return and volatility dynamics in the equity markets of Ghana, Kenya, Nigeria and South Africa; the interdependence between the equity and currency markets of Ghana and Nigeria and their sensitivity to negative news; and time varying jumps in the equity markets of Egypt, Nigeria and South Africa.

---

[1] The GDP figures were culled from IMF World Economic Outlook Publication, April 2011 located at http://www.imf.org/external/pubs/ft/weo/2011/01/pdf/text.pdf.

After correcting for thin trading, we find a limited degree of equity market linkages. Own market volatility is pronounced, and volatility is persistent in all the equity markets. Also, for Ghana and Nigeria, we find linkages between the equity and currency markets, and that political and ethnic violence related to negative news affect the first and the second moment of the foreign exchange and equity markets of Ghana and Nigeria. Furthermore, we find that jump sensitivity is persistent in the equity markets of Egypt, Nigeria and South Africa, but only South Africa is more likely to exhibit asymmetric jump volatility.

Also, the presence of thin trading provides spurious estimates, and in some cases it understates the economic significance of the jumps dynamics. Furthermore, we find that thin trading affects the estimation of the models. In particular, we find significant serial correlation in the standardised residuals, and the asymmetric model failed to capture all the asymmetry in the non-adjusted returns when the return and volatility dynamics in the equity markets of Ghana, Kenya, Nigeria and South Africa were examined. The same ame was also found when the interdependence between the equity and currency markets of Ghana and Nigeria and their sensitivity to negative news was investigated. Clearly, thin trading may be the cause of these bias estimates as Lo and Mackinlay (1990) stated in their study that thin or nonsynchronous trading induces spurious correlation in daily returns. Scholes and Williams (1977), and Dimson (1979) also reported biased estimation when securities are subject to thin trading.

The rest of the introductory part of this thesis is organised as follows: Section Two captures the issue of thin trading, Section Three presents a brief overview of theory, and Section Four discusses the three essays and their main findings.

2 THE ISSUE OF THIN TRADING

Thin trading may be the outcome of nonsynchronous trading where stocks trade at every consecutive interval, but not necessarily at the close of each interval. Alternatively, thin trading results from non-trading when stocks do not trade at every consecutive interval (Appiah-Kusi and Menya, 2003).

Table 1. Data Characteristics on the Stock Exchanges from the Years 2006 to 2010

Year	Country	Date market opened	Number of listed companies	Market capitalization in US$ billion	Trading volume million	Turnover ratio (%)	Market capitalization as % of GDP
Year 2010							
	Egypt	1898	373	84.10	33.43	42.9	40.46
	Ghana	1990	34	13.68	330.62	0.01	44.88
	Kenya	1954	55	14.48	75.45	9.45	48.29
	Nigeria	1960	217	66.20	93.34	8.00	31.00
	South Africa	1887	407	101.21	71.25	44.64	12.45
Year 2009							
	Egypt	1898	306	91.08	36.60	49.90	48.10
	Ghana	1990	35	11.15	0.97	2.10	73.70
	Kenya	1954	55	10.97	3.16	4.59	36.58
	Nigeria	1960	266	47.75	102.85	23.38	39.79
	South Africa	1887	410	91.08	36.60	49.90	29.30
Year 2008							
	Egypt	1898	373	85.84	24.49	70.30	53.00
	Ghana	1990	35	14.91	0.55	2.10	109.00
	Kenya	1954	56	10.98	5.87	11.42	31.81

Nigeria	1960	213	41.90	193.14	21.86	41.90
South Africa	1887	425	549.20	85.78	71.84	19.59
Year 2007						
Egypt	1898	435	136.69	15.061	38.73	105.07
Ghana	1990	32	12.74	0.29	1.14	96.00
Kenya	1954	54	13.61	1.94	10.41	64.43
Nigeria	1960	212	105.65	138.00	28.21	84.00
South Africa	1887	422	802.37	71.10	142.70	28.28
Year 2006						
Egypt	1898	595	93.35	9.08	48.70	80.00
Ghana	1990	32	0.12	0.10	0.42	97.00
Kenya	1954	52	11.41	1.45	11.45	69.39
Nigeria	1960	202	40.32	35.70	14.70	28.28
South Africa	1887	401	889.94	13.15	42.08	34.49

Source: The African Security Exchanges Association year books located at http://www.africansea.org/asea/library.aspx

In Table 1, it can be seen from the turnover ratio that African equity markets are typically characterised by thin trading, illiquidity and wider spread, which may lead to greater price impact, overreaction and insider trading. For example, the turnover ratios in Table 1 show that all the equity markets suffer from thin trading and low liquidity. Appiah-Kusi and Menya (2003), and Mlambo and Biekpe (2005, 2007) have documented pervasive thin trading and illiquidity on the equity markets of Ghana, Egypt, Kenya, Nigeria and South Africa.

Many studies have come to a consensus that thin or infrequent trading can cause serious bias in empirical work. Scholes and Williams (1977) find that thin or nonsynchronous trading introduces the potentially serious econometric problem of errors in variables. Similarly, Dimson (1979) posits that beta estimates are often severely biased when parameters are estimated from data which contain shares that are traded infrequently. Also Lo and MacKinlay (1990) show that thin or nonsynchronous trading induces spurious correlation in daily returns. Intuitively, technical trading strategies are profitable when markets are inefficient, but, in the presence of thin trading, the strategies break down and become unprofitable.

Cohen, Hawawini, Schwartz and Whitcomb (1983) and Miller, Muthuswamy and Whaley (1994) are among the number of studies that have proposed methods for adjusting for thin trading. However, McInish and Wood (1986) argue that the Cohen et al. (1983) method provides a minimal reduction in the magnitude of bias in beta estimates. The Miller et al. (1994) model, which basically fits an AR(1) model and uses the residuals from the regression to generate estimates of the innovations at the index level as embraced by Appiah-Kusi and Menya (2003), Al-Khazali, Ding and Pyun (2007) and Rayhorn, Hassan, Yu and Janson (2007) is adopted in this study.

3 BRIEF OVERVIEW OF THEORY AND MODELS

The Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982), and generalised into a parsimonious GARCH by Bollerslev (1986), is according to Poon and Granger (2003), a sophisticated time series model. They argue that the ARCH model and its various extensions formulate the conditional variance, σ_t^2, of returns through a maximum likelihood function instead of making use of the sample standard deviations. Thus, assume that stock market returns, r_t, are generated by an autoregressive process (AR) as follows:

$$r_t = \alpha + \beta r_{t-1} + \varepsilon_t, \tag{1}$$

where return innovations, $\varepsilon_t = \sigma_t v_t$, $v_t \sim WN(0,1)$, and the conditional variance, $\sigma_t^2 \equiv E_{t-1}[\varepsilon_t^2]$. The conditional variance σ_t^2 is a linear function of the past squared innovations. Thus:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \,. \tag{2}$$

For covariance stationarity, $\sum_{1=1}^{q} \alpha_i \leq 1$ and $\alpha_0, \alpha_i \geq 0$. A statistically significant coefficient for α_i denotes the presence of ARCH in the residuals.

Due to the non-negativity constraint of coefficients, which might impose a fixed large structure, and the large number q which might be required for empirical applications, Bollerslev (1986) introduced the GARCH (*p, q*) model, which is a generalization of the ARCH models. In the GARCH (*p, q*) model, the conditional variance is equal to a linear function of past squared residuals as well as its own past realization. This parsimonious model allows for flexible lag structure and longer memory. In the GARCH (*p, q*) model, the evolution of the conditional variance, σ_t^2, process is represented as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \,. \tag{3}$$

Although the GARCH (p, q) model allows for volatility clustering, it suffers from the inability to detect sign-bias asymmetry, and the non-negativity constraints on the coefficients could limit the application of the model. Nelson (1991) introduced the exponential GARCH (EGARCH), which basically specifies the conditional variance, σ_t^2, in logarithmic form and removes the need to impose non-negativity and invertibility constraints as in GARCH (1,1). Thus, the EGARCH is able to capture the stylised features such as volatility clustering, leptokurtosis effect, leverage effect and long run memory effect present in financial time series data. The Exponential GARCH (p, q) model, which is robust to standard errors, has the conditional variance, σ_t^2, modelled as follows:

$$ln\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i f(z_{t-1}) + \sum_{j=1}^{q} \beta_j ln\sigma_{t-j}^2, \quad (4)$$

where $f(z_{t-1}) = |z_{t-1}| - E|z_{t-1}| + \delta z_{t-1}$ and $z_{t-1} = \varepsilon_{t-1}/\sigma_{t-1}$.

3.1 *Multivariate VAR-EGARCH Model*

The first paper in this thesis applies EGARCH in the multivariate form with vector auto-regression (VAR). Specifically, essay one applies multivariateVAR-EGARCH (MVAR-EGARCH) model similar to Koutmos (1996). Using the return, $r_{i,t}^{adj}$ where i = 1, 2, 3, 4 (1 = Ghana, 2 = Kenya, 3 = Nigeria and 4 = South Africa), the multivariate VAR-EGARCH model is set up as follows

$$r_{i,t}^{adj} = \beta_{i,0} + \sum_{j=1}^{4} \beta_{i,j}\, r_{i,t-1}^{adj} + \varepsilon_{i,t,} \quad (5)$$

$$\sigma_{i,t}^2 = exp\left[\alpha_{i,0} + \sum_{j=1}^{4} \alpha_{i,j}\, f_j(z_{j,t-1}) + \gamma_i \ln\,(\sigma_{i,t-1}^2)\right], \quad (6)$$

$$f_j\left(z_{j,t-1}\right) = \left(\left|z_{j,t-1}\right| - E\left|z_{j,t-1}\right| + \delta_j z_{j,t-1}\right), \quad (7)$$

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t}, \quad (8)$$

$$\text{for } i, j = 1, 2, 3, 4 \text{ and } i \neq j,$$

where the innovation at time t, $\varepsilon_{i,t} = r_{i,t}^{adj} - \mu_{i,t}$ and standard innovation, $z_{i,t} = \varepsilon_{i,t}/\sigma_{i,t}$. The conditional mean and the conditional variance are represented by $\mu_{i,t}$ and $\sigma_{i,t}^2$ respectively and $\sigma_{i,j,t}$ is the conditional covariance between markets i and j. The correlation between $i \neq j$ is assumed to be constant.

Equation (5) denotes the vector autoregression (VAR) of the adjusted returns for the four markets, where the conditional mean in each market is a function of past own adjusted returns and cross-market past adjusted returns. Equation (5) depicts the EGARCH representation of the variance of $\varepsilon_{i,t}$ where the conditional variance of each market's returns is an exponential functional of past own, and cross-market standardised innovations. The function $f_j(z_{j,t-1})$ in Equations (5) and (6) is the asymmetric function of past standardised innovations, $E|z_{j,t-1}|$ is the expected absolute value of $z_{j,t-1}$, and $|z_{j,t-1}| - E|z_{j,t-1}|$ measures the magnitude effect of an innovation. The contemporaneous relationship between the returns of the four markets, which makes the model parsimonious, is captured in Equation (8).

3.2 Bivariate VAR-EGARCH Model with Dummy Variable

Essay two employs a bivariate VAR-EGARCH model to capture the simultaneous effects of return and volatility spillovers between the equity and the currency markets. A dummy variable is included in the model to capture the sensitivity of the equity and the foreign exchange markets to negative news. Consider the return, $r_{i,t}^{adj}$ where i = 1, 2 (1 = equity market and 2 = foreign exchange market) and the dummy denotes negative news, the bivariate VAR-EGARCH model with a dummy variable where the dummies are inserted in turns is as follows:

$$r_{i,t}^{adj} = \beta_{i0} + \sum_{j=1}^{2} \beta_{ij} r_{j,t-1}^{adj} + \varphi_i Dummy_t + \varepsilon_{i,t,} \quad \text{for } i,j = 1, 2 \text{ and } i \neq j, \tag{9}$$

$$\sigma_{i,t}^2 = exp\left[\alpha_{i,0} + \sum_{j=1}^{2} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2) + \phi_i Dummy_t\right], \tag{10}$$
$$\text{for } i,j = 1, 2 \text{ and } i \neq j.$$

Equation (9) captures the short-run dynamic relationships between the stock returns and the exchange rate. In this model, the conditional mean in each market is a function of past own returns, cross market past returns and negative news sensitivity. The term β_{i0} represents the long-term drift coefficients and the lead-lag relationships are captured by coefficients β_{ij} for i, j = 1, 2 and $i \neq j$. Equation (10) is the conditional variance equation which allows own standardised as well as cross standardised innovations from the other market to exert asymmetric impact on the volatility. If $\alpha_{i,j}$, for i, j = 1, 2 and $i \neq j$ is significantly different from zero, then volatility of market j will spill over to market i. The coefficient ϕ_i captures market i's volatility sensitivity to negative news. The functional f_j is an asymmetric function of past standardised innovations. Current innovations are given as $z_{i,t} = \varepsilon_{i,t}/\sigma_{i,t}$. The sign and size effects of the lagged innovations are captured by the following function:

$$f_j(z_{j,t-1}) = (|z_{j,t-1}| - E|z_{j,t-1}| + \delta_j z_{j,t-1}). \tag{11}$$

Antoniou, Pescetto and Violaris (2003) argue that the multi(bi)variate VAR-EGARCH model is free from a-priori restrictions on the structure of relationships among variables under consideration. The multi(bi)variate VAR-EGARCH model is flexible enough to capture the dynamics of the conditional variances and covariances. It also, for instance, permits the joint modelling of movements in two or more markets to determine whether first and second moment innovations in one market are indicative of the conditional mean and variance in other markets.

In modelling with multi(bi)variate VAR-EGARCH models, parsimony, which often means simplification, is sacrificed for flexibility. Thus, because the number of parameters in the multi(bi)variate VAR-EGARCH model increase rapidly with the dimension of the model, parsimony, which models with only a few parameters, may not be able to detect the relevant dynamics in the covariance structure. In place of parsimony, we assume that the conditional covariance matrix is decomposed into conditional standard deviations and correlations. This nests the constant correlation model of Bollerslev (1990), which is time invariant, and the conditional covariance matrix can be expressed as follows:

$$H_t = D_t S_t D_t, \tag{12}$$

where D_t is diagonal and the square of each element follows a univariate GARCH process. Thus $D_t = diag(h_{1t}^{\frac{1}{2}}, \dots, h_{Nt}^{\frac{1}{2}})$, and the correlation matrix, $S = [\rho_{ij}]$ is positive definite with ρ_{ii}= 1, i = 1,..., N. This implies that the off-diagonal elements of the conditional covariance matrix are denoted as follows:

$$[H_t]_{ij} = h_{it}^{\frac{1}{2}} h_{jt}^{\frac{1}{2}} \rho_{ij}, \quad i \neq j\ , \tag{14}$$

where $1 \leq i, j \leq N$.

Engle (2002) proposes the dynamic correlation model (DCC) where the conditional correlation is time variant, hence making it flexible as compared to the constant correlation model (CCC). In the first two essays of the thesis, however, we employ the constant correlation model because, unlike the DCC, the CCC parameterises the conditional correlation rather than the conditional covariances. Also, the CCC is easy to estimate, assures a positive semi-definite variance-covariance matrix and it can be combined with any variance specification.

3.3 Autoregressive Jump Intensity GARCH Model

The third essay, which applies the Chan and Maheu (2002) methodology, mixes univariate GARCH with autoregressive jump intensity. Chan and Maheu (2002) argue that the GARCH parameterisation explains the smooth changes in the volatility, and the jump captures the infrequent large discrete movements in asset returns. The GARCH-jump mixture methodology has been applied by Jorion (1988), Vlaar and Palm (1993), and Nieuwland, Vershchoor and Wolff (1994) where they assume that a constant jump distribution process directs the jump probability through time.

Bates (1991), however, found that jump behaviour is time varying before the 1987 crash using Standard and Poor 500 option futures and assuming underlying jump diffusion. Subsequent studies such as Das (1998), Fortune (1999) and Chernov, Gallant, Ghysels and Tauchen (1999) extended the theoretical work to allow for time-varying distributions. Chan and Maheu (2002) argue that their autoregressive-jump intensity GARCH methodology which assumes that return generation follows a Poisson process and, therefore, time varying has an ARMA functional form which is capable of parsimoniously capturing several forms of autocorrelation. Also, the model is easy to estimate and makes available maximum likelihood estimates and asymptotic inference. Consider the following model:

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i \, r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}. \tag{15}$$

where $z_t \backsim NID(0,1)$ and the h_t follows a GARCH (p, q) (Bollerslev, 1986) process. Thus,

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i}, \tag{16}$$

where $\epsilon_t = r_t^{adj} - \mu - \sum_{i=1}^{T} \phi_i \, r_{t-i}^{adj}$. The n_t, which describes the discrete number of jumps that arrive between $t-1$ and t, follows a Poisson distribution with $\lambda_t > 0$ and density

$$p(n_t = j|\Phi_{t-1}) = \frac{\lambda_t^j}{j!} e^{-\lambda_t}, \qquad j = 0,1,2, \ldots \tag{17}$$

where λ_t called the jump intensity is the mean and variance of the Poisson random variable. A constant jump-intensity model with $\lambda_t = \lambda$, $\theta_t = \theta$ and $\delta_t^2 = \delta^2$, and three variants of time varying jump intensity models are applied. For the latter, the jump-intensity, λ_t, is assumed to follow the autoregressive process

$$\lambda_t = \lambda_0 + \sum_{i=1}^{u} \rho_i \, \lambda_{t-i} + \sum_{i=1}^{v} \gamma_i \, \xi_{t-i} \, . \tag{18}$$

The jump intensity residual ξ_t is calculated as

$$\xi_{t-i} \equiv E[n_{t-1}|\Phi_{t-1}] - \lambda_{t-i} = \sum_{j=0}^{\infty} jP(n_{t-i}|\Phi_{t-i}) - \lambda_{t-i}.$$

Using observation r_t and the Bayes rule, the probability of the occurrence of j jumps at time t can be defined as

$$P(n_t = j|\Phi_t) = \frac{f(r_t|n_t=j,\Phi_{t-1})P(n_t=j|\Phi_{t-1})}{P(r_t|\Phi_{t-1})}$$

$$\text{for } j = 0,1,2, \ldots, \tag{19}$$

where $P(n_t = j|\Phi_t)$ is from equation (16). The distribution of the jump size, which follows a Gaussian, may change and display conditional dynamics. The following permits the conditional mean and conditional variance of the jump size distribution to be conditionally normal and a function of past returns,

$$\theta_t = \eta_0 + \eta_1 r_{t-1} D(r_{t-1}) + \eta_2 r_{t-1}\big(1 - D(r_{t-1})\big) \tag{20}$$

and

$$\delta_t^2 = \zeta_0^2 + \zeta_1 r_{t-1}^2, \tag{21}$$

where $D(x) = 1$ if $x > 0$ and 0 otherwise, and $\eta_0, \eta_1, \eta_2, \zeta_0$ and ζ_1 are parameters to be estimated. This specification of the conditional mean of the jump size provides some flexibility with regards to where jumps are centred.

4 BRIEF OVERVIEW OF EQUITY MARKETS AND DATA

The equity markets in Africa have grown from 5 in 1989 to 23 as the end of 2011 and the South African equity market is the developed and the most dominant one. For instance, as at the end of 2010 total market capitalisation for the South African equity market was USD101.21 billion and that of Egypt, the second largest in terms of capitalisation, was USD84.10 billion. In terms of turnover ratio as a measure of liquidity, South Africa has the highest followed by Egypt as at the end of 2010[2]. In the past, most of the equity markets used in this study, namely Egypt, Ghana, Kenya, Nigeria, and South Africa, used manual trading systems. This does not only negatively affect operational efficiency and liquidity; it also slows down trade and information production. Encouragingly, all the five markets have an electronic platform for trading, clearing and settlement of trade as at the end of 2010.

[2] See the African Security Exchanges Association 2009 Year book located at: http://www.africansea.org/asea/Library/ASEA_Yearbook2010.pdf

Daily Time Series Graphs for Egypt, Ghana, Kenya, Nigeria and South Africa Covering the Period 1st January 2001 to 31st December 2010

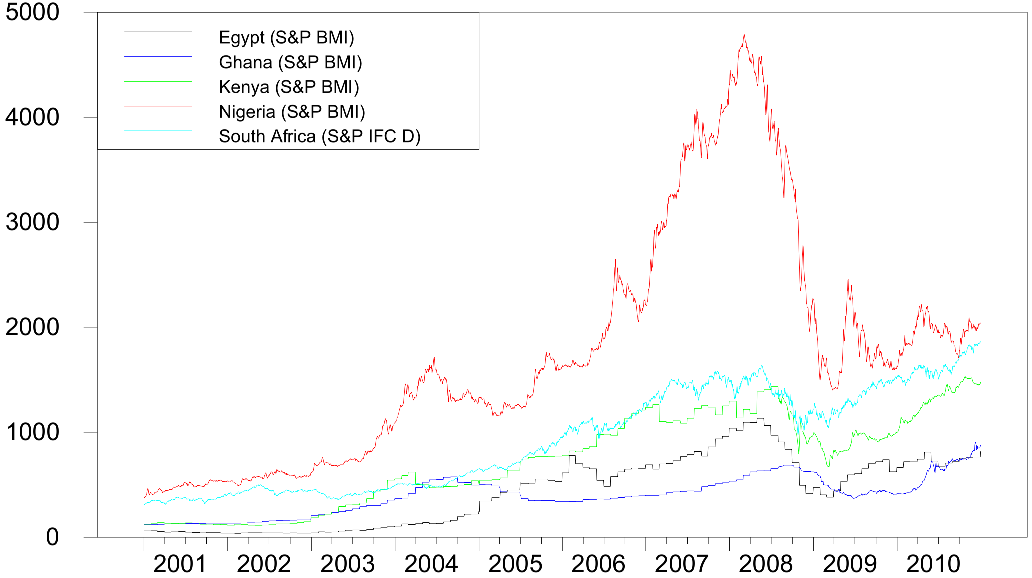

Figure 1. Time Series Graphs for Egypt, Ghana, Kenya, Nigeria and South Africa

Figure 1 depicts the daily time series graphs of the total equity return for Egypt, Ghana, Kenya, Nigeria and South Africa, covering the period 1st January 2001 to 31st December 2010. Generally, the graphs show that total returns increased steadily from 2001 to 2005 for all the equity markets. In particular, all the markets experienced their highest return in 2008. The impact of the global financial crisis of 2008 was felt by all the markets in 2009. Implied, these five markets lagged behind the major world financial markets in terms of the impact of the financial downturn. All the markets, with the exception of Nigeria, have their total returns climb steadily after 2009.

5 SUMMARY OF ESSAYS

This PhD thesis, Essays on Volatility and Time Varying Conditional Jumps in Thinly Traded African Financial Markets, consists of three essays. All the three essays are single authored. Below is a brief overview of the essays and their contribution to the literature.

5.1 Return and Volatility Dynamics among Four African Capital Markets: A Multivariate VAR-EGARCH Analysis

In this essay, the return and volatility dynamics was examined in the equity markets of Ghana, Kenya, Nigeria and South Africa. These four markets were chosen to reflect the similar legal regime which is based on Anglo-Saxon jurisprudence. In addition, these four markets are the biggest in terms of volume and value of equity traded on equity markets in sub-Saharan Africa. We apply a multivariate VAR-EGARCH model similar to that of Koutmos (1996) after correcting for thin trading using the method suggested by Miller et al. (1994).

The main findings suggest a reciprocal return stimuli spillover between Ghana and Kenya, as well as between Nigeria and South Africa. In the first moment, South Africa seems to be the dominant one. In particular, South Africa passes on past return innovations to Kenya and Nigeria but receives none. In the second moment, however, Nigeria appears to be the dominant one. Specifically, Nigeria exports volatility stimuli to Kenya and South Africa and receives none. Kenya, which has a statistically significant leverage effect, exports volatility stimuli to Ghana. Clearly, this implies that bad news from Kenya increases volatility on the equity market of Ghana more than good news of equal magnitude from the same source. We also find that for Ghana, Nigeria and South Africa, own volatility spillover coefficients seemed to be highest showing that changes in volatility in the four markets from domestic shocks are comparatively more important than the innovations from the other markets. The results also show significant volatility persistence in all four markets and the half-life of volatility is 36, 6, 13 and 51 days respectively for Ghana, Kenya, Nigeria and South Africa. When the MVAR-EGARCH model is applied to the logarithmic returns, we get spurious estimates. Impliedly, thin trading must be taken into account when modelling in an autoregressive framework.

By and large, the findings show a relatively limited degree of integration among the markets. The degree of integration is especially true for markets in different geographic areas on the Africa continent and not among markets that are geographically relatively close and belong to the same regional economic bloc as in the case of Ghana and Nigeria in the ECOWAS context[3]. Nonetheless, Hearn (2012) found segmentation of the equity markets in sub-Sahara Africa. Any percieved linkages may partly be due to nuances in the data as a result of the severe illiquidity.

The implication of these findings is that emerging and frontier market fund managers, and potential investors may benefit from portfolio diversification across the sub-Saharan equity markets. The results also suggest the possibility for increased co-operation among the various equity exchanges on the African continent to reduce the negative effect of asymmetric policy action by one exchange on the others.

5.2 Negative News, Equity and Foreign Exchange Markets Nexus: Evidence from Ghana and Nigeria

This essay complements the existing literature by studying the linkages between the equity and currency markets of Ghana and Nigeria and their sensitivity to negative news. Studies on equity and currency markets linkages in emerging markets have gained traction in recent times. In Africa, however, such study is at best scant. This

[3] The Economic Community of West African States (ECOWAS) is a regional group consisting of 15 independent states in West Africa with the aim of fostering economic integration and subsequently using a common currency modelled on the European Union

essay goes a step further by examining the equity and currency market linkages and their sensitivity to negative news. A bivariate VAR-EGARCH model with a dummy variable that captures the impact of negative news on the equity and currency markets is applied after correcting for thin trading using the method proposed by Miller et al. (1994). The negative news variables encompass political clashes, and inter and intra ethnic fighting in the case of Ghana, and for Nigeria, in addition to the factors enumerated for Ghana, we include religious violence and clashes between government security operatives and restive Niger delta militants.

The findings suggest that in the mean, there is a bi-directional relationship between the equity and foreign exchange markets of Ghana. We find current returns in the equity market being influenced by previous returns in the foreign exchange market of Nigeria. In the second moment, we find previous volatility in the equity market of Ghana influencing the current volatility in the foreign exchange market and not vice versa. We also find that political violence related negative news affects the equity and the currency markets of Nigeria, but for Ghana, it only affects the equity market.

Furthermore, ethnic violence related negative news affects respectively the returns of the equity and the foreign exchange markets of Ghana and Nigeria. Only the volatility in the foreign exchange markets of Ghana is sensitive to political violence related news. Volatility is persistent in all the markets for both countries, with the equity market of Ghana exhibiting volatility asymmetry. Further, when the bivariate VAR-EGARCH model was applied to the logarithmic return, the estimates were spurious. Moreover, as we indicated in essay one, thin trading needs to be taken into account to assure consistent and reliable estimates.

The findings contribute to the empirical literature on asset pricing, the risk-return performance of international equity and currency markets, and impact of news on financial markets. Specifically, European and American investors flocking to Africa will better appreciate the potential portfolio diversification implications of investing in the financial markets of Ghana and Nigeria, and the varied impact of negative news.

5.3 Time Varying Conditional Discrete Jumps in Emerging African Equity Markets

This essay explores the time varying conditional jumps in Egyptian, Nigerian and South African equity markets. Interestingly, these are the only markets in Africa classified as emerging. Similar to the first two papers, we correct for thin trading using the Miller et al. (1994) methodology, and we apply the autoregressive jump intensity-GARCH (ARJI-GARCH) of Chan and Maheu (2002). Specifically, we estimate a constant jump model and dynamic jump models.

The results suggest that conditional jumps are time varying, and jumps are sensitive to past shocks for the equity markets of Egypt and South Africa. For Nigeria, however, we find that the jump intensity is constant, and jumps become sensitive when the conditional mean and the conditional variance of the distribution are made functions of past returns. We find jump sensitivity to be persistent in all the equity markets, and only the equity market of South Africa displays jumps volatility asymmetry. The ARJI-GARCH model could not fully capture the heteroskedasticity when applied to the logarithmic (non-adjusted) returns, and we find that thin trading understates the economic significance of the jump for Nigeria in the case of the constant model. For the rest of the models, we obtained spurious estimates, which may be due to the impact of thin trading.

REFERENCES

Al-Khazali, O.M., D.K. Ding and C.S. Pyun, 2007, A New Variance Ratio Test of Random Walk in Emerging Markets: A Revisit, *Financial Review* 42: 303-317.

Antoniou, A., G. Pescetto and A. Violaris, 2003, Modelling International Price Relationships and Interdependencies between the Stock Index and Stock Index Futures Markets of Three EU Countries: A Multivariate Analysis, *Journal of Business Finance and Accounting,* 30 (5-6): 645-667.

Appiah-Kusi, J. and K. Menyah 2003, Return Predictability in African Stock Markets. *Review of Financial Economics*, 12(3): 247.

Bates, D.S., 1991, The crash of '87: Was it Expected? The evidence from Options Markets. *Journal of Finance*, 46: 1009–1044.

Bollerslev, T., 1986, Generalised Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics* 31: 307-327.

Bollerslev T., 1990, Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalised ARCH Model, *Review of Economics and Statistics*, 72(3): 498-505.

Canarella, G., S. M. Miller and S. K. Pollard, 2009, Dynamic Stock Market Interactions between the Canadian, Mexican, and the United States Markets: The NAFTA Experience Forthcoming, *Stock Returns: Cyclicality, Prediction, and Economic Consequences, Nova Science Publishers, Inc.*

Chan, W. H., 2008, Dynamic Hedging with Foreign Currency Futures in the Presence of Jumps, *Studies in Nonlinear Dynamics and Econometrics*, 12, article 4.

Chan, W.K. and J.M. Maheu, 2002, Conditional Jump Dynamics in Stock Market Returns, Journal *of Business and Economic Statistics*, 20: 377-379.

Chernov, M., A.R. Gallant, E. Ghysels and G. Tauchen, 1999, A New Class of Stochastic Volatility Models with Jumps: Theory and Estimation, *Working Paper CIRANO.*

Cohen, K. J., G. A. Hawawini, R. A. Schwartz and D. K. Whitcomb, 1983, Frictions in the Trading Process and the Estimation of Systematic Risk, *Journal of Financial Economics,* 12: 263-278.

Das, S.R., 1998, Poisson-Gaussian Processes and the Bond Markets, *Working Paper 6631*, National Bureau of Economic Research.

Dimson, E., 1979 Risk Measurement When Shares are Subject to Infrequent Trading, *Journal of Financial Economics* 7: 197-226.

Engle, R. F., 1982, Autoregressive Conditional Heteroskedasticity with Estimates of Variance of United Kingdom Inflation, *Econometrica,* 50: 987-1008.

Engle R. F., 2002, Dynamic conditional correlation: A Simple Class of Multivariate GARCH Models, *Journal of Business and Economic Statistics*, 20: 339-350.

Fortune, P., 1999, Are Stock Returns Different Over Weekends? A Jump Diffusion Analysis of the Weekend Effect, New *England Economic Review,* 5: 1-19.

Granger, C.W.J., B. Huang and C. Yang, 2000, A Bivariate Causality between Stock Prices and Exchange Rates: Evidence from Recent Asian Flu, *The Quarterly Review of Economics and Finance* 40: 337-354.

Hearn, B., 2012, Size and Liquidity Effects in African Frontier Equity Markets, *Applied Financial Economics, 22(9), 681-707.*

Jorion, P., 1988, On Jump Processes in the Foreign Exchange and Stock Markets, *Review of Financial Studies*, 1(4): 427–445.

Koutmos, G., 1996, Modelling the Dynamic Interdependence of Major European Stock Markets, *Journal of Business Finance and Accounting*, 23: 975-988.

Lin, C-T and Y-H. Lee, 2010, The Jump-diffusion Process for the VIX and the S&P 500 Index *African Journal of Business Management* 4(9): 1761-1768

Lo, A and A. C. MacKinlay, 1990, An Econometric Analysis of Infrequent Trading, *Journal of Econometrics* 45: 181-211.

Maheu, J. M and T. McCurdy, 2004, News Arrival, Jump Dynamics, and Volatility Components for Individual Stock Returns, *The Journal of Finance* 59: 755-793.

McInish, T.H. and R.A. Wood, 1986, Adjusting for Beta Bias: An Assessment of Alternate Techniques: A Note, *Journal of Finance* 41: 277-286.

Miller, M. H., J. Muthuswamy and R.Whaley, 1994, Mean Reversion of Standard and Poor 500 Index Basis Changes: Arbitrage-Induced or Statistical Illusion, *Journal of Finance*, 49: 479-513.

Mishra, K. A., 2004, Stock Market and Foreign Exchange market in India: Are they related? *South Asia Economic Journal* 5(2): 209-232.

Mlambo, C. and N. Biekpe, 2005, Thin Trading on African Stock Markets: Implications for Market Efficiency Testing, *Investment Analyst Journal*, 61: 29-40.

Mlambo, C. and N. Biekpe, 2007, Thin Trading on African Stock Markets: Implications for Market Efficiency Testing, *Investment Analyst Journal* 66: 5-18.

Nelson, D. B., 1991, Conditional Heteroskedasticity in Asset Returns; A New Approach, *Econometrica*, 59(2): 347–370.

Nieuwland, F.G.M.C., W.F.C. Verschoor and C.C.P. Wolf, 1994, Stochastic Trends and Jumps in EMS Exchange Rates, *Journal of International Money and Finance*, 13: 699-727

Phylaktis, K. and F. Ravazzolo, 2005, Stock Prices and Exchange Rate Dynamics, *Journal of International Money and Finance* 24: 1031-1053.

Poon, S.-H. and C.W.J. Granger, 2003, Forecasting volatility in Financial markets, *Journal of Economic Literature* 41: 478-539.

Rayhorn, C., M.K. Hassan, J.S. Yu and K.R. Janson, 2007, Emerging Market Efficiencies: New Zealand's Maturation Experience in the Presence of Non-linearity, Thin Trading and Asymmetric Information, *International Review of Finance* 7: 21-34.

Rao, A., 2008, Analysis of Volatility Persistence in Middle East Emerging Equity Markets, Studies *in Economics and Finance*, 25(2): 93-111.

Scholes, M. and J. Williams, 1977, Estimating Betas from Nonsynchronous Data, *Journal of Financial Economics* 5: 309-328.

Stoll, H. R. and R. Whaley, 1990, The Dynamics of Stock Index Futures Returns, *Journal of Financial and Quantitative Analysis* 25: 441-468.

Vlaar, P.J.G. and F.C. Palm, 1993, The Message in Weekly Exchange Rates in the European Monetary System: Mean Reversion, Conditional Heteroskedasticity, and Jumps, *Journal of Business Statistics,* 11 (3): 351–360.

PART II: THE ESSAYS

Return and Volatility Dynamics Among Four African Equity Markets: A Multivariate VAR-EGARCH Analysis

Saint Kuttu

Hanken School of Economics, Department of Finance and Statistics, P.O. Box 287, FIN-65101 Vaasa, Finland. Phone: +358(0)403521758, Fax: +358(6)3533703, Email: saint.kuttu@hanken.fi

June 8, 2012

Abstract

A multivariate VAR-EGARCH is used to examine the returns and volatility dynamics between thin traded adjusted equity returns from Ghana, Kenya, Nigeria and South Africa. The findings suggest a reciprocal return spillover between Ghana and Kenya, and Nigeria and South Africa. Also, Nigeria appears to be the source of volatility innovations for Kenya and South Africa. Thus, geographic proximity and membership of an economic regional bloc do not occasion market linkages in the case of Ghana and Nigeria. Own market volatility is pronounced, and volatility is highly persistent in all the four markets with Ghana and Kenya exhibiting volatility asymmetry.

Keywords: returns, volatility, interdependence, thin trading, equity.

JEL classification: E37, G14, G15

*I am grateful to Professors Johan Knif (my research supervisor), Kenneth Högholm and Mika Vaihekoski, Farrukh Javed, participants at the 18th Multinational Finance Conference in Rome, Italy, Graduate School of Finance 2009 Winter workshop in Oulu, Finland, and Hanken 2010 Spring Finance Seminar in Vasa, Finland for useful comments. I am also grateful to professor Gregory Koutmos for providing me with the RATS™ codes. Financial support from the Hanken Foundation, the Centre for Financial Research, Hanken, and Marcus Wallenbergs Stiftelse för Företagsekonomisk Forskning is gratefully acknowledged. All errors and omissions are solely mine.

1. INTRODUCTION

Interdependency of international equity markets was re-enforced by the 2008 global financial meltdown. In particular, the spasms of 2008 stock market volatility that spread from the U.S. equity market to other equity markets around the world became possible due to advances in computer technology and liberalisation of capital movements. As a consequence, a clear understanding of the extent of stock markets linkage and interaction will continue to be an essential consideration for international investors and policy makers.

A growing number of studies have attempted to establish the nature and extent of interdependence among international equity markets by applying multivariate heteroskedastic models. For instance, Canarella, Miller and Pollard (2009) studied the intra American markets. For the Asian markets, Rao (2008) and Worthington and Higgs (2004) investigated the volatility dynamics. Booth, Martikainen and Tse (1997a) and Koutmos (1996) examined the volatility dynamics of markets in Europe.

Despite the increased study of market interdependencies in America, Asia and Europe, very few studies have been undertaken on equity markets in Africa. In particular, Humavindu (2006), Adjasi and Beikpe (2006), Piesse and Hearn (2005) and Wang, Yang and Bessler (2003) have attempted to investigate stock market linkages in Africa in a univariate framework.

Unlike prior studies, this paper intends to contribute to the literature on market interdependencies by taking account of the thin-trading characteristic of the markets and examine the return transmission and volatility spillover between the equity markets of Ghana, Kenya, Nigeria and South Africa in a multivariate framework. We focus on these countries because of the cross-listing of stocks on these exchanges (see table 1).

Table 1. Securities Cross Listed on the Equity Markets under Study as of the End of 2010

Securities	Ghana	Kenya	Nigeria	South Africa
Anglogold Ashanti	Yes			Yes
British Oxygen company Limited		Yes	Yes	
Ecobank Transnational Inc.	Yes		Yes	
Guinness	Yes		Yes	
Marshall Limited		Yes		Yes
Stanbic (Standard Bank Group)			Yes	Yes
Standard Chartered Bank	Yes	Yes		
Total Oil	Yes	Yes		

The motivation for this study is twofold. Firstly, no study has examined the return and volatility dynamics contemporaneously on African stock exchanges in the multivariate vector autoregressive exponential GARCH (MVAR-EGARCH). Secondly, this study adjusts for thin trading[4]. Prior studies that attempted to model data from the equity markets of Ghana, Kenya, Nigeria and South Africa in an autoregressive framework that did not adjust for thin trading. Moreover given the biases associated with thin trading (Lo and MacKinlay, 1990), the validity of the findings may be questionable.

The empirical findings show a reciprocal return spillover between Ghana and Kenya, and Nigeria and South Africa. Kenya is also influenced by past return innovations from Nigeria and South Africa. In terms of volatility, Nigeria appears to be the source of volatility stimuli to Kenya and South Africa but not to Ghana. This is surprising because Ghana and Nigeria are geographically close, and they also belong to the same regional bloc. Nevertheless, there is no interdependency. The findings also show that, compared to cross-market volatility spillover, own market volatility innovations appear to be important in the market of Ghana, Nigeria and South Africa. Only the equity markets of Ghana and Kenya were found to exhibit volatility asymmetry.
These findings may be of benefit to emerging and frontier markets fund managers and international investors who are keen on pursuing international diversification. It may also help policy makers who are involved in making decisions on these exchanges.

[4] Appiah-Kusi and Menya (2003), and Mlambo and Biekpe (2005) have documented pervasive thin trading on the equity exchanges of Ghana, Nigeria and Kenya.

The rest of the study is organised as follows: Prior studies of equity markets linkages in Africa are presented in Section Two, modelling issues and empirical methodology are discussed in Section three, Section Four captures the data and its preliminary statistical properties, Section Five presents and discusses the empirical findings, and lastly, Section Six captures the conclusion.

2. PRIOR STUDIES OF EQUITY MARKETS LINKAGES IN AFRICA

In Africa, studies on equity market interdependencies are scant and tend to focus on first moment dynamics. The very few that include second moment dynamics examine the markets in a univariate modelling framework. For example, Humavindu (2006) used daily closing indices of the Namibian and South African equity markets from January 4, 1999, to March 20, 2003, and reports evidence of linear relationships, significant volatility spillover and strong correlation between the two markets, after applying a unit root test, cointegration analysis and an EGARCH model cannot be supported.

Similarly, Piesse and Hearn (2005) found that the equity markets of South Africa and Nigeria transmit volatility to the equity markets of Botswana, Ghana, Kenya, Malawi, Mauritius, Namibia, Zambia and Zimbabwe when they applied an EGARCH model on a data set spanning the period January 1993 to January 2000.

Also, Adjasi and Beikpe (2006), using a data set that included South Africa (large market) and Ghana (smaller market), report considerable cointegration relations between the larger markets and the smaller markets with significant feedback and causal effects both ways.

Likewise, Wang, Yang and Bessler (2003) employed cointegration and generalised impulse response functions on a data set that included the US as a global proxy. They find that regional integration between the stock markets of South Africa, Egypt, Morocco, Nigeria and Zimbabwe was weakened after the 1997–1998 crisis, with South Africa exerting significant influence on the other markets after the crisis.

Also, using Johansen cointegration and Granger Causality tests, Piesse and Hearn (2002) find the monthly stock indices of the equity markets of South Africa, Botswana and Namibia to be cointegrated, with causality running from Namibia to South Africa and not vice versa.

The analysis thus far indicates that African market volatility dynamics have not been contemporaneously examined in a multivariate modelling framework, despite the superior qualities of the MEGARCH of allowing investigation of the asymmetric impact of past innovations on current volatility spillover (Christofi and Pericli, 1999).

3. MODELLING ISSUES AND EMPIRICAL METHODOLOGY

3.1 Return Calculation and Thin Trading

Returns, r_t are calculated using the first difference of the natural logarithm of the total return index multiplied by 100. Thus,

$$r_t = \ln \left(I_t / I_{t-1}\right) * 100 \tag{1}$$

where I_t and I_{t-1} represent the current day's close total return index and the previous day's close total return index respectively. We focus on the logarithmic total index return because it is more tractable when linking together sub-period returns to form returns over long intervals. Also, it is more likely to be stationary over time which is essential for the modelling technique employed in this study.

The former adduced reason, however, may not hold in the presence of thin trading; thus, nonsynchronous trading and non-trading which is a feature of emerging market and therefore symptomatic of African markets (see turnover ratio of below 50% for all four equity markets in Table 3)[5] can induce serial correlation in the return series which would normally exhibit serial independence. Ignoring this phenomenon can result in substantial bias inferences drawn from empirical work (Lo and MacKinlay, 1990).

---

[5] Appiah-Kusi and Menya (2003) document pervasive thin trading in the equity markets of Ghana, Kenya, Nigeria and South Africa.

Cohen, Hawawini, Schwartz, and Whitcomb (1983) and Miller, Muthuswamy and Whaley (1994) are among the number of studies that have proposed methods for adjusting for thin trading. McInish and Wood (1986) posit that the Cohen et al. (1983) methodology provides a minimal reduction in the magnitude of bias in beta estimates. Hence, to deal with nonsynchronous trading and non-trading, we adopt Miller, Muthuswamy and Whaley's (1994) model as embraced by Appiah-Kusi and Menya (2003), Al-Khazali, Ding and Pyun (2007) and Rayhorn, Hassan, Yu and Janson (2007). Miller et al. (1994)[6] show that, to eliminate the effect of thin trading, a moving average (MA) model that mirrors the number of non-trading days is needed. Miller et al. (1994) have shown that, the MA is equivalent to estimating an autoregressive model of order (1) to obtain the thin trading adjustment. Thus,

$$r = \alpha + \beta r_{t-1} + \varepsilon_t. \tag{2}$$

Using the residuals (ε_t) from Equation (2), the adjusted returns are estimated as follows:

$$r_t^{adj} = \varepsilon_t/(1-\beta), \tag{3}$$

where r_t^{adj} is the return at time t adjusted for thin trading and assumes that the non-trading adjustment required to correct the return for thin trading is constant over time. According to Antoniou, Ergul and Holmes (1997), this assumption may not hold for illiquid African equity markets where adjustment is more likely to be time dependent; hence, we employ the recursive least squares estimation technique in estimating Equation (2).

[6] See Miller et al. (1994) for proof

3.2 Multivariate VAR-EGARCH Model

The Autoregressive Conditional Heteroskedasticity model of Engle (1982) and the Generalised ARCH (GARCH) model of Bollerslev (1986) are popular in modelling second moment dynamics in stock returns because they are parsimonious, and they capture stylised facts such as thick tails, volatility clustering and persistence in stock returns. They are also very flexible in terms of allowing different parameterisation, but they cannot detect sign-bias asymmetry and the non-negativity constraints could limit the application of the model.

Nelson (1986), however, introduced the Exponential GARCH (EGARCH) model which imposes no parameter and sign restrictions, allows for the oscillatory behaviour of the variance, permits volatility asymmetry and is more robust to deviation to standard errors. In the spirit of Koutmos (1996), we combine vector autoregressive (VAR) with EGARCH in the form of multivariate VAR-EGARCH (MVAR-EGARCH) for this study.

This model permits the joint modelling of movements in two or more markets to determine whether return innovations and volatility in one market are indicative of the conditional first moment and conditional second moment in other markets. According to Antoniou, Pescetto and Violaris (2003), the MVAR-EGARCH model is also free from a priori restrictions on the structure of relationships among variables under consideration. Using the return, $r_{i,t}^{adj}$, where i = 1, 2, 3, 4 (1 = Ghana, 2 = Kenya, 3 = Nigeria and 4 = South Africa), we set up the multivariate VAR-EGARCH model in the spirit of Koutmos (1996) as follows:

$$r_{i,t}^{adj} = \beta_{i,0} + \sum_{j=1}^{4} \beta_{i,j}\, r_{i,t-1}^{adj} + \varepsilon_{i,t,} \tag{4}$$

$$\sigma_{i,t}^2 = exp\left[\alpha_{i,0} + \sum_{j=1}^{4} \alpha_{i,j}\, f_j(z_{j,t-1}) + \gamma_i \ln\left(\sigma_{i,t-1}^2\right)\right], \tag{5}$$

$$f_j\left(z_{j,t-1}\right) = \left(\left|z_{j,t-1}\right| - E\left|z_{j,t-1}\right| + \delta_j z_{j,t-1}\right), \tag{6}$$

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t}, \tag{7}$$

for $i, j = 1, 2, 3, 4$ and $i \neq j$,

where the innovation at time t, $\varepsilon_{i,t} = r_{i,t}^{adj} - \mu_{i,t}$ and standard innovation, $z_{i,t} = \varepsilon_{i,t}/\sigma_{i,t}$. The conditional mean and the conditional variance are represented by $\mu_{i,t}$ and $\sigma_{i,t}^2$

respectively and $\sigma_{i,j,t}$ is the conditional covariance between markets i and j. The correlation between $i \neq j$ is assumed to be constant.

Equation (4) denotes the vector autoregression (VAR) of the adjusted returns for the four markets, where the conditional mean in each market is a function of past own adjusted returns and cross-market past adjusted returns. A significant $\beta_{i,j}$, which captures the lead-lag relationship, would mean that current return in market j can be used to predict future return in market i. The persistence in volatility is measured by γ_i, and the time period required for shocks to decrease to one half of the original size in market i, for instance, is quantified by the half-life given as: $\ln(0.5)/\ln(\gamma_i)$. The impact of innovation in market i on the volatility of market j is measured by $\beta_{i,j}(1+\delta_j)$ for a 1% positive innovation and $\beta_{i,j}|-1+\delta_j|$ for a 1% negative innovation and that of degree of volatility asymmetric impact of negative and positive innovations is also measured by $|-1+\delta_j|/(1+\delta_j)$.

The EGARCH representation of the variance of $\varepsilon_{i,t}$ is captured by Equation (5) where the conditional variance of each market's returns is an exponential functional of past own and cross-market standardised innovations. The functional, $f_j(z_{j,t-1})$ in Equations (5) and (6) is the asymmetric function of past standardised innovations, $E|z_{j,t-1}|$ is the expected absolute value of $z_{j,t-1}$, and $|z_{j,t-1}| - E|z_{j,t-1}|$ measures the magnitude effect of an innovation. Intuitively, if $\alpha_{i,j}$ is positive, the impact of $z_{j,t-1}$ on conditional variance will be positive (negative) if the magnitude $z_{j,t-1}$ is greater (smaller) than its expected absolute value, $E|z_{j,t-1}|$. The term $\delta_j z_{j,t-1}$ measures the sign effect. The parameter δ_j measures the asymmetric impact on the volatility of market i with the following partial derivatives:

$$\partial f_j(z_{j,t}) / \partial z_{j,t} = 1 + \delta_j, \text{ for } z_j > 0, \tag{8}$$

$$\partial f_j(z_{j,t}) / \partial z_{j,t} = -1 + \delta_j, \text{ for } z_j < 0. \tag{9}$$

Asymmetry exists if the coefficient δ_j, is negative and statistically significant. Thus, stock market decline in market j ($z_{j,t-1} < 0$) will be followed by higher volatility than stock market advances ($z_{j,t-1} > 0$). This phenomenon will be consistent with the leverage effect, whereby a market decline produces a higher aggregate debt-to-equity ratio and, hence, higher volatility (Koutmos, 1996), or the risk premium effect where news of increasing volatility reduces the demand for a stock because of risk aversion. Volatility spillover across markets is measured by $\alpha_{i,j}$, for $i, j = 1, 2, 3, 4$ and $i \neq j$. A statistically significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovation in market j increases volatility in market i more than a positive innovation of an equal magnitude. Additionally, a negative $z_{j,t}$ coupled with a negative δ_j, increases the size effect and the reverse holds true.

The conditional covariance specification in Equation (7) captures the contemporaneous relationship between the returns of the four markets. It implies that the covariance is proportional to the product of the standard deviations of markets i and j. This assumption greatly makes the estimation of the model parsimonious and it is plausible for many applications (Bollerslev, Chou and Kroner, 1992). With this simplification however, the number of parameters to be estimated is fifty-four and assuming normality and a sample of $\mathcal{T}$ observations, the log likelihood function for the VAR-EGARCH model can be written as

$$L(\Theta) = -0.5(\mathcal{NT})\ \ln 2\pi - 0.5 \sum_{t=1}^{T} (ln|S_t| + \varepsilon_t' S_t^{-1} \varepsilon_t)$$

where $\mathcal{N}$ is the number of the four equations and Θ, the 54 x 1 parameter vector to be estimated. $\varepsilon_t' = [\varepsilon_{1,t,} \varepsilon_{2,t,} \varepsilon_{3,t,} \varepsilon_{4,t}]$ is the 1 x 4 vector of innovations at time t, S_t the 4 x 4 time varying conditional variance-covariance matrix with diagonal elements given by Equation (5) for $i, j = 1, 2, 3, 4$ and $i \neq j$. The log likelihood function is highly non linear in Θ; we, therefore, use the Broyden, Fletcher, Goldfarb and Shanno (BFGS) algorithm (in RATS ™ 7.3) to maximise $L(\Theta)$ via Quasi-Maximum Likelihood Estimation (QMLE) which is robust to the distribution of the disturbance term. Bollerslev and Wooldridge (1992) have shown that, under a correct specification of the conditional mean and variance, consistent estimates of the parameters could be obtained via QMLE.

4 DATA

The study uses daily closing total return indices of four major African markets: Ghana (S&P BMI), Kenya (S&P BMI), Nigeria (S&P BMI) and South Africa (S&P IFCI D). The data set obtained from DataStream, which is adjusted for dividends is denominated in US dollars. The data ranges from August 1st, 2005, to July 30th, 2010, yielding 1,305 observations. We focus on total return indices because it reflects the impact of divided and regulatory changes on the market as a whole; this impact will not be captured if we use prices of individual companies. Also, for consistency, the base period for the data for the study is set at 1st August 2005. The reason is that, unlike the other exchanges that trade five times a week prior to 1st August 2005, trading on the Ghana stock exchange changed from three times a week to five times a week on that date. To assure uniformity and consistent estimates, we set 1st August 2005 as the base period for all markets.

4.1 Profile of the Various Exchanges

Table 2 summarises the information and the structure of operations on the markets covered. Trading hours appear rather short for Ghana, Kenya and Nigeria. This is a reflection of the relatively small number of companies listed on the exchanges. Although the markets covered trade electronically, local stock brokerage firms form the intermediary between investors and the equity markets. South Africa does not tax dividend for residents, whereas Ghana, Kenya and Nigeria have a dividend tax ranging from 5% to 10%. Only Kenya has restrictions on foreign participation.

Table 2. Institutional and Trading Arrangement on Sample Country Equity Markets at the End of 2010.

Market	Trading hours	Trading Method	Settlement cycle*	Index	Tax Rates (dividends, interest, capital gain)	Restrictions on Foreign Participation
Ghana	09:30-12:00. Mon-Fri	Continuous Auction Automated Trading System and Electronic Clearing/Settlement.	T + 3	GSE All Share	8% Withholding tax on dividend, No tax on capital gains till 2010.	No
Kenya	09:00 -15:00. Mon-Fri	Intra-day Trading, Online Trading.	T + 5	KSE All Share	Dividends 5% (domestic investors), 10% (foreign investors); interest 15%; capital gains suspended.	Yes
Nigeria	09:30 -14:30. Mon-Fri	Intra-day Trading, Online Trading.	T + 3	NSE All Share	10% on dividend, no capital gains tax.	No
South Africa	09:00 -17:00. Mon-Fri	Margin Trading, Intra-day Trading, Online Trading, Short Selling and Borrowing.	T + 5	JSE All Share	No taxes imposed on dividends for Non Residents, Interest 12%; Royalties, Visiting Entertainers 5%.	No

Source: The African Security Exchanges Association located at http://www.africansea.org/asea/library.aspx
*Represent the number of days that clearing and settlement for equities are conducted.

Table 3. Descriptive Data on the Stock Exchanges from Years 2007 to 2009.

Year	Country	Date market opened	Date index established	Number of listed companies	Market capitalization in US$ billion	Trading volume million	Turnover ratio (%)	Market capitalization as % of GDP
Year 2009								
	Ghana	1990	1990= 100	35	11.15	0.97	2.10	73.70
	Kenya	1954	1964= 100	55	10.97	3.16	4.59	36.58
	Nigeria	1960	1993= 100	266	47.75	102.85	23.38	39.79
	South Africa	1887	1960= 100	390	801.27	82.59	47.90	29.30
Year 2008								
	Ghana	1990	1990= 100	35	14.91	0.55	2.10	109.00
	Kenya	1954	1964= 100	56	10.98	5.87	11.42	31.81
	Nigeria	1960	1993= 100	213	80.60	193.14	21.86	41.90
	South Africa	1887	1960= 100	425	549.20	83.78	71.84	19.59
Year 2007								
	Ghana	1990	1990= 100	32	12.74	0.287	1.14	96.00
	Kenya	1954	1964= 100	54	13.61	1.94	10.41	64.43
	Nigeria	1960	1993= 100	212	105.60	138.00	28.21	84.00
	South Africa	1887	1960= 100	422	802.37	71.20	142.70	28.28

Source: The African Security Exchanges Association located at http://www.africansea.org/asea/library.aspx

Table 3 presents the descriptive data on the exchanges. As can be seen, all the equity markets suffer from thin trading with Ghana, Kenya and Nigeria having relatively low turnover ratios, thus reflecting the low level of liquidity on the exchanges.

4.2 Preliminary Statistical Properties of the Data

As a necessary condition for the application of the multivariate VAR-EGARCH model, we check for unit root, and the augmented Dickey-Fuller (1979) test decisively rejects the null of unit root in all samples.
Panel A of Table 4 provides the summary statistics for the adjusted return series. While each of the series displays "stylised" facts common to many financial markets such as non-normality depicted by fat tails, there are noticeable differences between them. The markets display positive standard deviations, but the level of risk is noticeably different. For instance, South Africa has the highest risk with a standard deviation of 2.57 with Ghana having the least of 1.06.

Negative shocks are more common than positive shocks in Nigeria and South Africa, and investors have higher probability of receiving negative returns from these equity markets whereas the equity markets of Ghana and Kenya exhibit positive skewness. It worth noting that the markets of Ghana and Kenya have undertaken some positive initiatives in recent years to improve the depth, efficiency and liquidity of the markets and these have led to an increase in market capitalization from USD 0.083 billion and USD6.14 billion in 2005 to USD14.91 billion and USD10.98 billion 2008 for Ghana and Kenya respectively. Clearly, the graphs in Figures 1, 2, 3 and 4 show that all the four markets bottom out of the global financial crises in 2009.

Leptokurtic behaviour which implies adjusted returns has high probability of getting outliers, is higher than normal, and it is apparent in all the series with a pronounced fat tail for Kenya. The Jarque-Bera statistic shows that the hypothesis of normality is decisively rejected for all the four markets. This rejection makes a nonlinear modelling methodology more plausible.

Table 4. Summary Statistics and Correlation Matrix of Adjusted Returns for the Period 1st August, 2005, to 30th July, 2010

Panel A:	Summary	Statistics		
Statistic	Ghana	Kenya	Nigeria	South Africa
Mean	0.014	-0.050	-0.049	-0.145
Median	-0.010	-0.119	0.031	-0.190
Std. Dev.	1.055	1.787	2.355	2.568
Skewness	0.609	1.034	-0.192	-0.382
Kurtosis	24.474	38.482	7.192	6.590
Jarque-Bera	20702.3**	68690.0**	963.6**	732.6**
LB(12) for $r_{i,t}^{adj}$	19.987**	18.677**	19.760**	21.615**
LB(12) for ${r_{i,t}^{adj}}^2$	23.185**	17.343**	983.760**	288.900**
Arch (p)	0.084**	0.090**	0.216**	0.261**
ADF	-31.651**	-31.651**	-35.217**	-33.311**
Panel B:	**Unconditional**	**Correlations**		
Ghana	1.00	0.131**	-0.022**	0.035**
		(36.125)	(-32.651)	(12.274)
Kenya		1.00	0.050**	0.021**
			(26.960)	(19.915)
Nigeria			1.00	0.093**
				(16.724)
South Africa				1.00

**denotes statistically significant at 5%, Arch (p) is the Engle (1982) test for ARCH up to lag order 1 and ADF denotes Augmented Dickey Fuller unit root test.

The unconditional correlations between the four markets are reported in panel B of Table 4. The correlations are not only significant to portfolio managers but to international investors as well. Because the degree of correlation between the markets may help in the construction of investment portfolios and hedging strategies in order to benefit from diversification. The scope of diversification between the markets is relatively wide as depicted by the relatively low pair-wise unconditional correlation between the equity markets of Ghana and Nigeria; Kenya and Nigeria; and Kenya and South Africa.

The Ljung-Box (LB) statistics show that there is autocorrelation in the return and squared return series for all the markets. This is usually interpreted as evidence of the presence of ARCH effects in the conditional volatility; hence, we formally perform the ARCH test of Engle (1982) which is distributed as χ^2. The results confirm the presence of conditional heteroskedasticity in the series for all markets at lag one.

Chaotic and random innovations cannot be distinguished by the Ljung-Box statistical test. To distinguish between the white noise and white chaos, which will help identify the type of the nonlinear structure and, hence, improve the formulation of the model, we use the BDS test developed by Brock, Dechert and Scheimkman (1996) which is based on a null hypothesis of independent and identically distributed (IID) to test for the presence of nonlinear dependence in the return. The epsilon values, which range from half to two times the standard deviation, are reported for 2 to 6 correlation dimensions in Table 5. The results confirm the presence of nonlinear innovations at a 5% level of significance in the return series.

Table 5. BDS Test for Nonlinearity for the Period 1st August, 2005, to 30th July, 2010

	BDS	Statistic		
Correlation Dimension	Ghana	Kenya	Nigeria	South Africa
2	0.041**	0.048**	0.010**	0.023**
	(10.490)	(13.200)	(5.637)	(11.657)
3	0.0777**	0.0838**	0.0175**	0.0298**
	(14.379)	(15.090)	(9.486)	(14.996)
4	0.0964**	0.1056**	0.0173**	0.0279**
	(16.978)	(16.529)	(21.421)	(18.567)
5	0.1023**	0.1128**	0.0137**	0.2178**
	(19.578)	(17.542)	(14.788)	(21.831)
6	0.100**	0.113**	0.001**	0.016**
	(22.461)	(18.898)	(17.140)	(26.679)

**denotes statistically significant at 5% and numbers in parenthesis are z-statistics

To determine whether an asymmetric model is required to test the response of the variance of past shocks, we use the sign and size bias tests developed by Engle and Ng (1993). This test considers the sign effect, where past shocks of different signs have a different effect on the present volatility, and the size effect, where past shocks of the same sign but different magnitudes have a different effect on the present variance. We estimate a symmetric GARCH (1, 1) model of Bollerslev (1986) for the series and apply the tests on the estimated standardised residuals defined as $\hat{v}_t = (\hat{\varepsilon}_t/\hat{\sigma}_t)$,where $\hat{\varepsilon}_t$ and $\hat{\sigma}_t$ are the residuals and standard deviations of the series respectively.

We define s_{t-1}^{-} as a dummy indicator that takes the value of 1 if $\hat{\varepsilon}_{t-1}$ is negative and zero otherwise. The significance or otherwise of ϕ_1 in Equation (10) will determine sign bias in

$$\hat{v}_{it}^2 = \phi_{i0} + \phi_{i1} s_{it-1}^{-} + u_{it}, \tag{10}$$

where u_{it} is the normally distributed error. The statistical significance of ϕ_{i1} will imply that positive and negative shocks to $\hat{\varepsilon}_{it-1}$ impact differently on the conditional variance. Similarly, statistically significant ϕ_{i1} in Equation (11) suggests the presence of negative size bias; thus, negative shocks of different magnitude have different effects on the standardised residuals in

$$\hat{v}_{it}^2 = \phi_{i0} + \phi_{i1} s_{it-1}^{-} \varepsilon_{it-1} + u_{it}. \tag{11}$$

Defining $s_{it-1}^{+} = 1 - s_{it-1}^{-}$ in Equation (11) so that s_{it-1}^{+} picks out the observations with positive innovations and the statistical significance of ϕ_{i1} in Equation (11) implies the presence of positive sign bias. Engle and Ng (1993) propose a joint test for sign and size bias using the following regression:

$$\hat{v}_{it}^2 = \phi_{i0} + \phi_{i1} s_{it-1}^{-} + \phi_{i2} s_{it-1}^{-} \varepsilon_{it-1} + \phi_{i3} s_{it-1}^{+} \varepsilon_{it-1} + u_{it}. \tag{12}$$

Statistical significance of ϕ_{i1} in Equation (12) indicates the presence of sign bias, where positive and negative shocks have differing impacts upon future conditional variance. Similarly, the significance of ϕ_{i2} and ϕ_{i3} would imply that size bias is present, where not only the sign but the magnitude of the shocks are important. The joint test statistic is obtained by multiplying the total number of observations by the R^2 of the regression of the squared standardised residuals which will asymptotically follow a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects on the three independent variables used in Equations (10) and (11).

Table 6. Volatility Specification Test for the Period 1st August, 2005, to 30th July, 2010

Statistic	Ghana	Kenya	Nigeria	South Africa
Size bias	0.306	-0.745**	0.243	-0.120
	(1.183)	(-2.132)	(1.769)	(-0.907)
Positive Sign bias	0.646**	0.736**	0.130**	0.213**
	(3.588)	(5.422)	(2.637)	(4.908)
Negative Sign bias	-0.516**	-0.163	-0.260**	-0.234**
	(-2.685)	(-1.022)	(-5.6745)	(-5.809)
Joint test, F[3, 1305]	9.332**	40.997**	19.226**	30.683**

**denotes statistically significant at 5% and numbers in parenthesis are *t*-statistics

Table 6 displays the results of tests for the asymmetric effect of new information on the squared standardised residuals as in Engle and Ng (1993). From the *t*-statistics in Table 5, it can be inferred that positive and negative innovations in all markets may have an additional effect on their own volatility beyond what is predicted by the symmetric GARCH model. In particular, the variance of return is larger after a positive shock in all the four markets. There is presence of negative size bias for all markets except Kenya, indicating that negative shocks, large and small, have different effects on the standardised residuals. It is, however, impossible to determine the source of these effects, since they are caused by both positive and negative innovations. Finally, the joint test is significant for all markets; hence, we can conclude that asymmetric effect on volatility exists and, to eliminate bias in the empirical work, a multivariate VAR-EGARCH model, which allows us to contemporaneously examine asymmetric effects on volatility in the four markets under consideration, is appropriate for the study.

5 EMPIRICAL FINDINGS

The maximum likelihood estimates of the MVAR-EGARCH model are reported in Table 7. The model considers both returns and asymmetric volatility spillovers. There is reciprocal spillover between Ghana and Kenya, and Nigeria and South Africa. Kenya is also influenced by past return innovations from Nigeria and South Africa. Similarly, Ghana is influenced by past return innovations from South Africa. This supports earlier findings by Adjasi and Beikpe (2006) that the South African stock market appears to have a dominating influence on the equity market of Ghana.

Thus, past return spillover from Kenya to Ghana was about 2.0%, whereas Kenya's returns were affected by 4.6% of Ghana's past return stimuli. Similarly, Nigeria and South Africa exported about 6.2% and 2.1% past return innovations respectively to the Kenyan equity market. Nigeria transmitted about 6.0% of return stimuli to the South African equity markets, whereas South Africa also transmitted 2.9% return innovations to the Nigerian equity market. Based on these results, we can argue that there exist feedback effects between Ghana and Kenya, and Nigeria and South Africa.

Furthermore, the role of South Africa as an information producer is considerable**.** This is not surprising because the South African equity market is the largest among the four markets in terms of market capitalisation and liquidity. Thus, South Africa exerts the greatest impact on the other markets and receives relatively the weakest influence from the others.

The second moment dynamics in all four markets show that, apart from Kenya, the conditional variances of the other equity markets are heavily influenced by their past innovations. There is also a unidirectional conditional volatility spillover from Kenya to Ghana; Nigeria to Kenya; and Nigeria to South Africa. These regional patterns in volatility are supported by Piesse and Hearn (2005) in respect of Nigeria and Ghana, in western Africa, being affected both by Kenya in the east and South Africa in the south. However, the findings do not support bidirectional volatility between Nigeria and South Africa. This is in contrast to results reported by Piesse and Hearn (2005) for the same equity markets.

Table 7. Quasi Maximum Likelihood Estimates of the MVAR-EGARCH Model.(Adjusted Returns) for the Period 1st August, 2005, to 30th July, 2010

$$r_{i,t}^{adj} = \beta_{i,0} + \sum_{j=1}^{4} \beta_{i,j}\, r_{i,t-1}^{adj} + \varepsilon_{i,t,}$$

$$\sigma_{i,t}^2 = exp\left[\alpha_{i,0} + \sum_{j=1}^{4} \alpha_{i,j}\, f_j(z_{j,t-1}) + \gamma_i \ln\,(\sigma_{i,t-1}^2)\right],\ \text{for } i,j = 1,2,3,4 \text{ and } i \neq j.$$

$$f_j(z_{j,t-1}) = \left(|z_{j,t-1}| - E|z_{j,t-1}| + \delta_j z_{j,t-1}\right),\quad \sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t},$$

Ghana		Kenya		Nigeria		South Africa	
$\beta_{1,0}$	0.041**	$\beta_{2,0}$	0.160**	$\beta_{3,0}$	-0.051	$\beta_{4,0}$	-0.096**
	(2.604)		(4.550)		(-1.807)		(-2.072)
$\beta_{1,1}$	-0.003	$\beta_{2,1}$	0.005**	$\beta_{3,1}$	0.062	$\beta_{4,1}$	-0.051
	(-1.112)		(3.869)		(1.853)		(-0.582)
$\beta_{1,2}$	0.015**	$\beta_{2,2}$	0.037**	$\beta_{3,2}$	0.0401	$\beta_{4,2}$	-0.055
	(3.547)		(3.247)		(0.602)		(-1.137)
$\beta_{1,3}$	0.0154	$\beta_{2,3}$	0.062**	$\beta_{3,3}$	-0.019**	$\beta_{4,3}$	0.061**
	(1.946)		(3.602)		(-2.216)		(2.022)
$\beta_{1,4}$	-0.018**	$\beta_{2,4}$	0.022**	$\beta_{3,4}$	0.029**	$\beta_{4,4}$	0.016
	(-2.409)		(2.987)		(3.679)		(0.859)
$\alpha_{1,0}$	-0.015	$\alpha_{2,0}$	0.104**	$\alpha_{3,0}$	0.083**	$\alpha_{4,0}$	0.0406**
	(-0.869)		(2.722)		(2.558)		(3.105)
$\alpha_{1,1}$	0.136**	$\alpha_{2,1}$	0.0591	$\alpha_{3,1}$	-0.0252	$\alpha_{4,1}$	0.031
	(2.111)		(0.772)		(-0.714)		(0.967)
$\alpha_{1,2}$	0.172**	$\alpha_{2,2}$	0.091	$\alpha_{3,2}$	0.062	$\alpha_{4,2}$	0.024
	(4.711)		(1.621)		(1.889)		(0.558)
$\alpha_{1,3}$	0.1725	$\alpha_{2,3}$	0.3903**	$\alpha_{3,3}$	0.2919**	$\alpha_{4,3}$	0.0935**
	(1.770)		(2.371)		(4.304)		(2.201)
$\alpha_{1,4}$	-0.079	$\alpha_{2,4}$	-0.141	$\alpha_{3,4}$	0.017	$\alpha_{4,4}$	0.098**
	(-0.675)		(-1.714)		(0.403)		(3.957)
δ_1	-0.683**	δ_2	-0.452**	δ_3	-0.159	δ_4	0.781
	(-4.997)		(-2.484)		(-1.389)		(1.672)
γ_1	0.981**	γ_2	0.904**	γ_3	0.949**	γ_4	0.986**
	(68.766)		(32.820)		(61.355)		(21.471)

**denotes statistically significant at 5% and numbers in parenthesis are *t*-statistics.

Own volatility spillover coefficients appear to be higher than cross-market volatility spillover coefficients. This indicates that changes in volatility in the equity markets of Ghana, Nigeria and South Africa are more important than external shocks. Further, Nigeria seems to be the source of cross-market volatility to the equity markets of Kenya and South Africa. Intuitively, this clearly shows that geographic proximity, coupled with similar legal regimes as is the case of Ghana and Nigeria may not matter when it comes to cross-market volatility transmissions.

Additionally, the returns and volatility transmission results do not support linkages between equity markets of countries belonging to an economic bloc. Ghana and Nigeria, for instance, belong to the Economic Community of West African States; neverthelsess there are no linkages in the first or second moment between their equity markets. This is in contrast with findings by Chukwuogor-Ndu and Kasibhatla (2007), Darrat and Zhong (2005), Aggrawal and Kyaw (2005), and Gilmore and McManus (2004) where they find that the equity markets of countries within the North American Free Trade Agreement framework to be linked. Kenya and South Africa, on the other hand, belong to the East African Community and the Southern African Development Community respectively; nonetheless, they have strong linkages with Ghana and Nigeria in the first and second moments. This notwithstanding, Hearn 2012 has found that the equity markets in sub-Sahara Africa are segmented; hence, any percieved linkages may partly be due to the severe illiquidity foumd the equity markets in sub-Sahara Africa.

Interestingly, only Ghana and Kenya exhibit asymmetric volatility transmission, implying that negative shocks from these two markets have a greater impact on volatility than positive shocks of equal magnitude. This is consistent with the notion of leverage effect. Thus, negative innovations of stock prices in Ghana and Kenya respectively have an impact on their conditional volatility about five and three times larger than positive innovations[7].

Moreover since the asymmetric coefficient, δ_j, in the equity market of Nigeria and South Africa is not significant, there is no difference between positive and negative innovations for the respective markets. Given a unidirectional volatility spillover from

[7] Degree of volatility asymmetric impact of negative and positive innovations is calculated as $\left|-1+\delta_j\right|/(1+\delta_j)$.

Kenya to Ghana and a significant asymmetric parameter, δ_j, for Kenya, the total impact of innovations from Kenya to Ghana is about 25.0% and 9.0% for negative and positive news respectively, confirming the presence of information asymmetry.[8] The degree of volatility persistence for the four markets is closer to unity indicating very strong volatility persistence. Volatility shocks for Ghana, Kenya, Nigeria and South Africa respectively last for 36, 6, 13 and 51 days, on average, based on the half-life of shock[9].

Residual based robustness tests are depicted in Table 8. Panel A of Table 8 shows that the estimated mean and variance are approximately equal to zero and one respectively, and the Ljung-Box statistics for 12 lags show no dependence in the standardised and squared standardised residuals for the equity markets of all countries. Additionally, results from Panel B show no evidence of sign bias in the standardised residuals. The estimated conditional pairwise correlations of the standardised residuals depicted in Panel C are lower than the unconditional estimates reported in Panel B of Table 3. Thus, the correlation between Kenya and South Africa reduced from 0.0209 to 0.0062, similar reductions are observed for the rest of the coefficients. This is consistent with Koutmos (1996), and we can attribute these phenomena to improvements resulting from the application of the multivariate VAR-EGARCH model.

8 The impact of innovations is given as $\alpha_{ij}(1+\delta_j)$ for a 1% positive innovation and $\alpha_{ij}\left|-1+\delta_j\right|$ for a 1% negative innovation.
9 Half-life of shock is calculated as $\ln(0.5)/\ln(\gamma_i)$.

Table 8. Robustness Tests for the Period 1st August, 2005, to 30th July, 2010

Panel A. Model Diagnostics

	Ghana	Kenya	Nigeria	South Africa
Mean	0.006	0.086	0.010	0.002
Variance	1.012	0.979	1.006	0.989
LB[12] for $Z_{i,t}$	20.209	7.153	2.538	14.988
LB[12] for $Z_{i,t}^2$	16.722	2.538	16.598	2.538

Panel B. Volatility Specification Test Based on the News Impact Curve

Test	Ghana	Kenya	Nigeria	South Africa
Sign Bias	-0.084	-0.626	-0.144	-0.023
	(-0.353)	(-0.467)	(-0.612)	(-0.218)
Negative Size bias	-0.138	0.058	0.059	-0.076
	(-0.798)	(0.543)	(0.737)	(-0.391)
Positive Size bias	0.155	0.073	0.115	0.091
	(0.940)	(0.095)	(0.379)	(0.603)
Joint Test, F[3, 1305]	0.632	0.272	0.722	0.663

Panel C. Conditional Correlation of Standardised Residuals

	Ghana	Kenya	Nigeria	South Africa
Ghana	1.000	0.123**	-0.001**	0.017**
		(31.449)	(-22.047)	(10.263)
Kenya		1.000	0.033**	0.006**
			(16.673)	(15.205)
Nigeria			1.000	0.076**
				(13.743)
South Africa				1.000

** denote statistically significant at 5%. Numbers in parenthesis are *t*-statistics.

Table 9. Maximum Likelihood Estimates of the MVAR-EGARCH Model (Non Adjusted Return Series) for the Period 1st August, 2005, to 30th July, 2010

$$\mathrm{r}_{i,t} = \beta_{i,0} + \sum_{j=1}^{4} \beta_{i,j}\, \mathrm{r}_{i,t-1} + \varepsilon_{i,t,}$$

$$\sigma_{i,t}^2 = exp\left[\alpha_{i,0} + \sum_{j=1}^{4} \alpha_{i,j}\, f_j(z_{j,t-1}) + \gamma_i \ln\,(\sigma_{i,t-1}^2)\right], \quad \text{for } i,j = 1,2,3,4 \text{ and } i \neq j.$$

$$f_j(z_{j,t-1}) = \left(|z_{j,t-1}| - E|z_{j,t-1}| + \delta_j z_{j,t-1}\right), \quad \sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t},$$

	Ghana		Kenya		Nigeria		South Africa
$\beta_{1,0}$	0.047**	$\beta_{2,0}$	0.140**	$\beta_{3,0}$	0.0706	$\beta_{4,0}$	0.076
	(4.322)		(6.223)		(1.841)		(1.898)
$\beta_{1,1}$	-0.040**	$\beta_{2,1}$	0.006	$\beta_{3,1}$	0.077**	$\beta_{4,1}$	-0.004
	(-2.440)		(0.221)		(2.874)		(-0.075)
$\beta_{1,2}$	0.037**	$\beta_{2,2}$	0.122**	$\beta_{3,2}$	0.124**	$\beta_{4,2}$	-0.023
	(3.124)		(3.658)		(2.564)		(-0.835)
$\beta_{1,3}$	0.014	$\beta_{2,3}$	0.042**	$\beta_{3,3}$	0.004	$\beta_{4,3}$	0.0292
	(1.339)		(7.654)		(0.162)		(1.722)
$\beta_{1,4}$	0.030**	$\beta_{2,4}$	-0.044**	$\beta_{3,4}$	-0.043	$\beta_{4,4}$	0.424**
	(5.566)		(-5.648)		(-1.446)		(3.141)
$\alpha_{1,0}$	-0.009	$\alpha_{2,0}$	0.0749	$\alpha_{3,0}$	0.145**	$\alpha_{4,0}$	0.0293**
	(-1.237)		(0.851)		(2.523)		(2.996)
$\alpha_{1,1}$	0.149**	$\alpha_{2,1}$	-0.166	$\alpha_{3,1}$	-0.070	$\alpha_{4,1}$	0.005
	(2.528)		(-0.752)		(-1.310)		(0.229)
$\alpha_{1,2}$	0.126**	$\alpha_{2,2}$	0.170	$\alpha_{3,2}$	0.119**	$\alpha_{4,2}$	0.054**
	(3.089)		(0.879)		(2.005)		(2.394)
$\alpha_{1,3}$	0.158**	$\alpha_{2,3}$	0.492**	$\alpha_{3,3}$	0.348**	$\alpha_{4,3}$	0.125**
	(2.174)		(2.768)		(3.590)		(3.266)
$\alpha_{1,4}$	-0.105**	$\alpha_{2,4}$	-0.108	$\alpha_{3,4}$	0.0328	$\alpha_{4,4}$	0.116**
	(-3.307)		(-1.225)		(0.705)		(3.372)
δ_1	-0.124**	δ_2	-0.064	δ_3	-0.213	δ_4	0.645
	(-4.432)		(-0.442)		(-1.258)		(1.741)
γ_1	0.988**	γ_2	0.854**	γ_3	0.912**	γ_4	0.981**
	(6.304)		(5.425)		(3.465)		(6.056)

**denotes statistically significant at 5% and numbers in parenthesis are *t*-statistics.

Further, we estimate the MVAR-EGARCH model on the non-adjusted returns series, and the results are shown in Table 9. The robustness check in Panel A of Table 10 shows a significant serial dependence in the standardised residuals for Ghana. Also the

Table 10. Robustness Tests (Non Adjusted Return Series) for the Period 1st August, 2005, to 30th July, 2010

Panel A: Model Diagnostics

	Ghana	Kenya	Nigeria	South Africa
Mean	-0.032	-0.053	0.001	-0.027
Variance	1.011	0.994	1.004	0.992
LB[12] for $Z_{i,t}$	29.694**	9.047	12.609	22.788
LB[12] for $Z_{i,t}^2$	2.190	2.531	2.531	2.531

Panel B: Volatility Specification Test Based on the News Impact Curve

Test	Ghana	Kenya	Nigeria	South Africa
Sign Bias	0.047	-0.600**	-0.332	-0.046
	(0.165)	(-2.077)	(-1.190)	(-0.443)
Negative Size bias	-0.219	0.079	0.072	-0.099
	(-1.021)	(0.527)	(0.758)	(-1.552)
Positive Size bias	0.034	0.087	0.128	0.203
	(0.164)	(0.652)	(1.252)	(2.755)
Joint Test, F[3, 1305]	0.388	1.457	0.629	3.163

**denotes statistically significant at 5% and numbers in parenthesis are *t*-statistics.

sign bias test in Panel B of Table 10 shows a significant size bias for Kenya. Clearly, the results in Table 10 shows that the MVAR-EGARCH model fails to capture the heteroskedasticity and the size bias present in the series of Ghana and Kenya respectively. Thus, failure to account for thin trading may results in inconsistent and unreliable estimates when the MVAR-EGARCH model is applied to data from a thinly traded equity market.

6 CONCLUSION

This paper examined the return dynamics and volatility transmission among the equity markets of Ghana, Kenya, Nigeria and South Africa. We adjusted for thin trading and applied a MVAR-EGARCH model to daily data of 1,305 observations. In particular, we examined own and cross first and second moment dynamics among the four markets.

The results show reciprocal return stimuli spillover between Ghana and Kenya, and Nigeria and South Africa. In the first moment, South Africa seems to be the dominant one exporting past return innovations to Kenya and Nigeria. Thus, South Africa's role as an information provider to the equity markets of Kenya and Nigeria is considerable.

In the second moment, however, Nigeria appears to be the dominant one. Specifically, Nigeria exports volatility stimuli to Kenya and South Africa and receives none in return. Kenya also exports volatility stimuli to Ghana, coupled with a statistically significant leverage effect for Kenya. Intuitively, this implies that bad news from Kenya increases volatility on the equity market of Ghana more than good news of equal magnitude from the same source. Also, for Ghana, Nigeria and South Africa, own volatility spillover coefficients seemed to be highest indicating that changes in volatility in the four markets from domestic shocks are comparatively more important than the innovations from the other markets.

The results also show significant volatility persistence in all four markets. Overall, the findings show that there is a relatively limited degree of integration among the markets. Also, we find that the equity markets of Ghana and Nigeria which falls within the ECOWAS regional bloc are not integrated both in the first and second moments. This is contrary to similar findings reported for other economic region blocs (See Chukwuogor-Ndu and Kasibhatla, 2007, for a study on the equity markets within the North American Free Trade Agreement). Any percieved linkages may be the result of nuances in data due to the severe illiquidity. This is because Hearn 2012 has documented that, the equityy markets in sub-Sahara Africa are segmented. We also find that the presence of thin trading affected the model estimation; hence, we obtained reliable and consistent estimates after adjusting for thin trading.

By and large, the results may highlight the possibility for increased co-operation among the various equity exchanges on the African continent to reduce the negative effect of asymmetric policy action by one exchange on the others.

One may argue that, as a result of the base period of the data set at 1st August 2005, the power of tests may have decreased due to the limited data used for the study. Studies in the future may consider employing longer data when it becomes available. The Dynamic Equicorrelation model of Engle and Kelly (2009) which restricts the correlations in Equation (7) to be equal contemporaneously across all variables, but not over time, should be considered for the modelling methodology.

REFERENCES

Adjasi, C. K. D. and N. B. Biekpe, 2006, Cointegration and Dynamic Causal Links amongst African Stock Markets, *Investment Management and Financial Innovations*, 3 (4): 102-119.

Aggrawal, R. and N. A. Kyaw, 2005, Equity Market Integration in the NAFTA Region: Evidence from Unit Root and Cointegration Tests, *International Review of Financial Analysis*, 4: 393–406.

Al-Khazali, O.M., D.K. Ding and C.S. Pyun, 2007, A New Variance Ratio Test of Random Walk in Emerging Markets: A Revisit, *Financial Review* 42: 303-317.

Antoniou, A., N. Ergul, and P. Holmes, 1997, Market Efficiency, Thin Trading and Non-linear Behaviour: Evidence from an Emerging Market, *European Financial Management*, 3(2): 175–190.

Antoniou, A., G. Pescetto and A. Violaris, 2003, Modelling International Price Relationships and Interdependencies between the Stock Index and Stock Index Futures Markets of Three EU Countries: A Multivariate Analysis, *Journal of Business Finance and Accounting,* 30 (5-6): 645-667.

Appiah-Kusi, J. and K. Menyah, 2003, Return Predictability in African Stock Markets, *Review of Financial Economics*, 12(3): 247.

Bollerslev, T., 1986, Generalised Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, 31: 307-327.

Bollerslev, T., Chou, R. and Kroner, F. K., 1992, ARCH Modelling in Finance, *Journal of Econometrics*, 52: 5-59.

Bollerslev, T. and J.M. Wooldridge, 1992, Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Variances, *Econometric Reviews* 11: 143-172.

Booth, G. G., T. Martikainen and Y. Tse, 1997a, Price and Volatility Spillovers in Scandinavian Stock Markets, *Journal of Banking and Finance*. 21: 811–823.

Brock, W., W. Dechert and J. Scheinkman, 1987, A Test for Independence Based On the Correlation Dimension, *Working Paper*, University of Wisconsin at Madison, University of Houston, and University of Chicago.

Canarella, G., S. M. Miller, and S. K. Pollard, 2009, Dynamic Stock Market Interactions between the Canadian, Mexican, and the United States Markets: The NAFTA Experience Forthcoming, *Stock Returns: Cyclicality, Prediction, and Economic Consequences, Nova Science Publishers, Inc.*

Christofi, A. and A. Pericli, 1999, Correlation in Price Changes and Volatility of Major Latin American Stock Markets, *Journal of Multinational Financial Management* 9: 79–93.

Chukwuogor-Ndu, C. and Kasibhatla, K. 2007, Post NAFTA Integration of North American Stock Markets: Implications for Financial Decision Making, *North American Journal of Finance and Banking Research*, 1.

Cohen, K. J., G. A. Hawawini, R. A. Schwartz, and D. K. Whitcomb, 1983, Frictions in the Trading Process and the Estimation of Systematic Risk, *Journal of Financial Economics,* 12: 263-278.

Darrat, A. F. and M. Zhong, 2005, Equity Market Linkage and Multinational Trade Accords: the Case of NAFTA, *Journal of International Money and Finance*, 24: 793–817.

Dickey, D.A. and W.A. Fuller, 1979, Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association*, 74: 427–431.

Engle, R. F., 1982, Autoregressive Conditional Heteroskedasticity with Estimates of Variance of United Kingdom Inflation, *Econometrica* 50: 987-1008.

Gilmore, C. G. and G. M. McManus, 2004, The impact of NAFTA on the Integration of the Canadian, Mexican and U.S. Equity Markets, *Research in Global Strategic Management*, 10: 137–151.

Hearn, B., 2012, Size and Liquidity Effects in African Frontier Equity Markets, *Applied Financial Economics, 22(9), 681-707.*

Humavindu, M., 2006, Integration and Volatility Spillovers in African Equity Markets: Evidence from Namibia and South Africa. *The African Finance Journal*, 8 (2): 31-51.

Koutmos, G., 1996, Modelling the Dynamic Interdependence of Major European Stock Markets, *Journal of Business Finance and Accounting*, 23: 975-988.

Kroner, K. and V. Ng, 1998, Modelling Asymmetric Comovements of Asset Returns. *Review of Financial Studies* 11: 817-844.

Lo, A and A. C. MacKinlay, 1990, An Econometric Analysis of Infrequent Trading, *Journal of Econometrics* 45: 181-211.

McInish, T.H., and R.A. Wood, 1986, Adjusting for Beta Bias: An Assessment of Alternate Techniques: A Note, *Journal of Finance* 41: 277-286.

Miller, M. H., J. Muthuswamy and R.Whaley, 1994, Mean Reversion of Standard and Poor 500 Index Basis Changes: Arbitrage-Induced or Statistical Illusion, *Journal of Finance*, 49: 479-513.

Mlambo, C. and N. Biekpe, 2005, Thin Trading on African Stock Markets: Implications for Market Efficiency Testing, *Investment Analyst Journal*, 61: 29-40.

Nelson, D. B., 1991, Conditional Heteroskedasticity in Asset Returns; A New Approach, *Econometrica*, 59(2): 347–370.

Piesse, J. and B. Hearn, 2002, Equity Market Integration versus Segmentation in Three Dominant Markets of the Southern African Customs Union: Cointegration and Causality Tests, *Applied Economics*. 14(1): 711-172.

Piesse, J. and B. Hearn, 2005, Integration and the Asymmetric Transmission of Volatility: A Study of Equity Markets in Sub Saharan Africa, *South African Journal of Economics,* 73(1): 36-53.

Rao, A. 2008, Analysis of Volatility Persistence in Middle East Emerging Equity Markets, *Studies in Economics and Finance*, 25(2): 93-111.

Rayhorn, C., M.K. Hassan, J.S. Yu and K.R. Janson, 2007, Emerging Market Efficiencies: New Zealand's Maturation Experience in the Presence of Non-linearity, Thin Trading and Asymmetric Information, *International Review of Finance* 7: 21-34.

Wang, Z., J. Yang, and D. A. Bessler, 2003, Financial Crisis and African Stock Market Integration, *Applied Economics Letters, 10(9): 527-533*.

Worthington, A. C. and H. Higgs, 2004, Transmission of Equity Returns and Volatility in Asian Developed and Emerging Markets: a Multivariate GARCH Analysis*,* *International Journal of Finance and Economics*, 9(1): 71-80.

Appendix A

Time Series Graphs for the Period 1st August 2005 to 30th July 2010 (Total Stock Market Return Index)

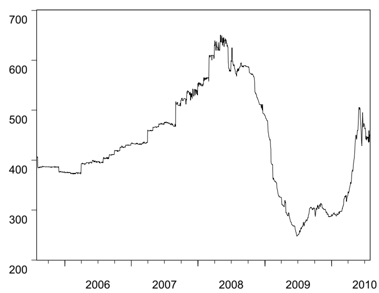

Figure 1. Ghana (S&P BMI)

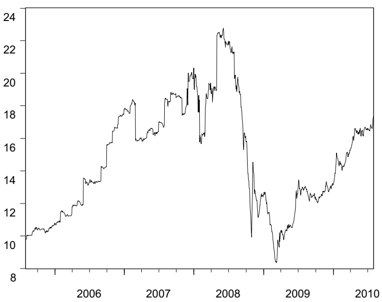

Figure 2. Kenya (S&P BMI)

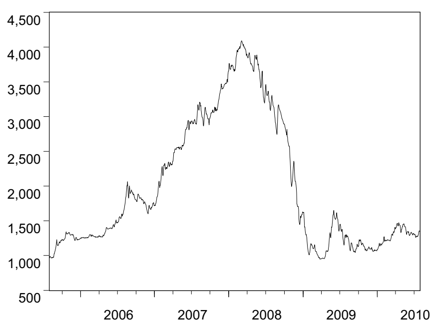

Figure 7. Nigeria (S&P BMI)

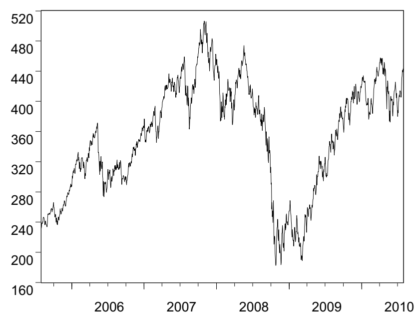

Figure 8. South Africa (S&P IFCI D)

Time Series Graphs for the Period 1st August 2005 to 30th July 2010 (Logarithmic Stock Retuns)

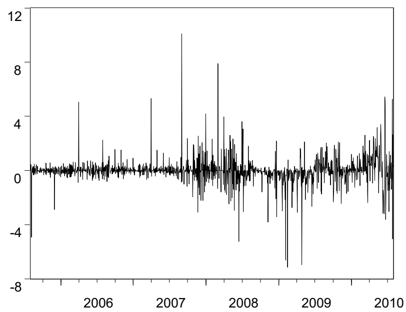

Figure 8. Ghana

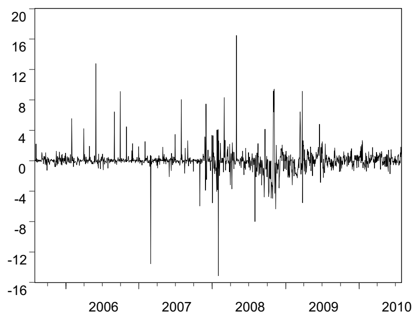

Figure 9. Kenya

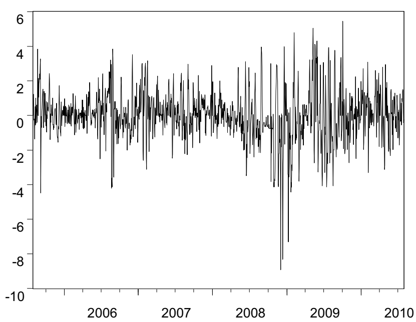

Figure 11. Nigeria

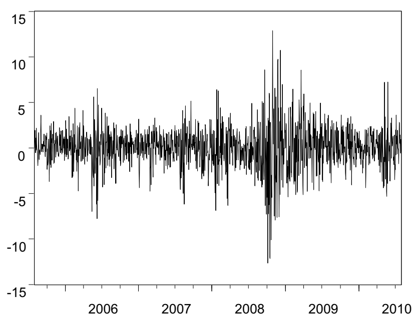

Figure 12. South Africa

Negative News, Equity and Foreign Exchange Markets Nexus: Evidence from Ghana and Nigeria.

Saint Kuttu

Hanken School of Economics, Department of Finance and Statistics, P.O. Box 287, FIN-65101 Vaasa, Finland. Phone: +358(0)403521758, Fax: +358(6)3533703, Email: saint.kuttu@hanken.fi

June 8, 2012

Abstract

A Bivariate VAR-EGARCH model with a negative news sensitivity dummy is used to examine the returns and volatility dynamics between the foreign exchange and the equity markets of Ghana and Nigeria. The findings for Ghana suggest a bidirectional return spillover between the equity and foreign exchange markets; also volatility spills over from the equity market to the foreign exchange market. For Nigeria, there is a unidirectional return spillover from the foreign exchange market to the equity market. Political and ethnic violence related negative news were found to impact the first and the second moment of the foreign exchange and equity markets of both countries.

Keywords: returns, volatility negative news, thin trading, equity, foreign exchange.

JEL classification: E37, F31, G14, G15

---

*I am grateful to Professors Johan Knif (my research supervisor), Kenneth Högholm, Björn Hansson and K.V. Bhanu Murthy, participants at the 2nd World Finance Conference, Rhodes, Greece, 2011 Nordic Finance Workshop, Helsinki, Finland and Hanken 2010 Autumn Finance Seminar, Vasa, Finland for useful comments. I am also grateful to Syed Mujahid Hussain for help with RATS™ coding. Financial support from the Hanken Foundation, Marcus Wallenbergs Stiftelse för Företagsekonomisk Forskning, and the Centre for Financial Research, Hanken is gratefully acknowledged. All errors and omissions are solely mine.

1 INTRODUCTION

Given that major emerging markets such as Brazil, Russia, India and China have high correlation with the developed markets (see Bhar and Nikolova, 2009), international investors are looking for ways to reduce their downside exposure by diversifying their investment portfolios into other emerging and frontier markets. Nigeria, the 7th world crude oil exporter and the third largest economy in Africa, and Ghana the 2nd world Cocoa and Gold producer (with significant discovery of offshore crude oil) have attracted increased attention from international investors. With the relative stability enjoyed by these two countries, coupled with strong institutional structures put in place to create an enabling business environment, international investors are venturing into these markets which were considered exotic about two decades ago.

By venturing into these markets, international investors have to grapple with equity and currency volatility risks. This is because any linkages between the equity and the currency market may affect how international investors and multinational corporations manage risk, whenever there are fluctuations in either the currency or equity market. Also, any dependence between the equity and currency markets may be used to predict the trajectory of exchange rate or stock market returns. Additionally, confidence reducing negative news have the potential to impact the equity and currency markets unfavourably; thus, if returns and exchange rates are driven by negative news asymmetrically, current investors have to re-balance their portfolio strategy, and firms, which depend on foreign exchange to import raw materials, expert labour and equipment, will have their share prices affected. Potential investors may also be weary of investing in markets that are unfavourably affected by negative news.

The emerging market literature on the contemporaneous relationship between currency and equity market provides mixed results. Studies such as Aydemir and Demirhan (2009), Phylaktis and Ravazzolo (2005), Mishra (2004) and Granger, Huang and Yang (2000) document significant positive relationships between stock returns and exchange rates. Conversely, Tabak (2006) and Doong, Yang and Wang (2005) have reported significant negative relationships between the two variables. Rahman and Uddin (2009) and Smyth and Nandha (2003), found very weak or no relationships between stock returns and exchange rates.

The seminal contribution by Karolyi and Stulz (1996) on the impact of economic news on U.S. and Japanese stock returns have caused studies on the sensitivity of equity and currency markets to news to gain traction in recent times. Albuquerque and Vega (2008), Boyd, Hu and Jagannathan (2005), Gwilym and Buckle (2001) and Clare and Courtenay (2001) are among the studies that have documented that equity returns react in varying degrees to both positive and negative macroeconomic news. Similarly, Bauwens, Omrane and Giot (2005), Andersen, Bollerslev, Diebold and Vega (2003), Cai, Cheung, Lee and Melvin (2001), Melvin and Yin (2000) and Evans and Lyons (1999) have come to a consensus that current news affect future exchange rate movements in varying degrees.

Studies on the nexus between the equity and currency markets in Africa are at best scant. For instance, Aliyu (2009) finds a long-run bi-directional relationship between stock return and exchange rates after applying Granger two step and Johansen and Juselius cointegration tests on data for Nigeria covering 1st January, 2001, to 31st December, 2008. Also, Adjasi, Harvey and Agyapong (2008) employed the univariate EGARCH model on data from March 2005 to June 2006 (low power of test given the small sample size) and find that a depreciation in the local currency leads to an increase in the stock market returns for Ghana. Similarly, applying a cointegration test on seven selected African countries, Ajasi and Biekpe (2005) find that a drop in the exchange rate leads to increases in the stock market returns in some countries in the long run, but in the short run some countries experience a reduction in the stock market returns when the exchange rate falls. On the impact of news on equity or currency markets in Africa, Kauffman and Weerapana (2005) was the only paper to attempt to investigate the impact of AIDS-related news on the South African Rand-Dollar exchange rate. Using a regression-based procedure on a data set that spans from 1st January, 1998, to 31st December, 2002, they find that AIDS-related negative news has a pronounced negative effect on the exchange rate whereas related positive news has little or no effect on the exchange rate.

From the foregoing, the motivation for this study is threefold. First, there have been no studies in the literature to examine the bi-directional relationships between the currency and equity markets for Ghana and Nigeria in particular, and Africa in general in a Bivariate VAR-EGARCH framework. Second, this is the first study to contemporaneously examine the impact of negative news on the mean and variance of the equity and currency markets of Ghana and Nigeria and, for that matter, Africa in general. Finally, this study takes thin trading into account. Previous studies that attempt to study the linkages between the equity and currency markets of Ghana and Nigeria did not account for thin trading. Given the biases associated with thin trading, inferences drawn from such studies may not be reliable.

This study examines the equity and foreign exchange markets of Ghana and Nigeria in two respects. Firstly, we investigate the first and second moment dynamics between the equity and currency markets, and, secondly, we examine the impact of negative news on the mean and variance of the equity and foreign exchange markets.

Mlambo and Biekpe (2005) and Appiah-Kusi and Menya (2003) have documented the presence of thin trading on the equity markets of these two countries, and, according to Lo and MacKinlay (1990), thin trading can introduce series of bias in empirical work. We, therefore, find it necessary to take thin trading into account before applying the Bivariate Vector Autoregressive Exponential Generalised Autoregressive Conditional Heteroskedasticity (Bivariate VAR-EGARCH) model. This method of analysis does not only provide more reliable estimates, it also allows us to model the contemporaneous relationship between the return and volatility in the two variables for the two markets. The flexibly of the model allows us to incorporate a dummy variable to examine the sensitivity of the equity and the currency markets to negative news.

The examination of negative news sensitivity comes on the heels of the fact that the investment world is bombarded with distressing images and information about inter- and intra-ethnic strife, religious violence and political conflicts in Africa. The distressing images and news about various conflicts have the potential of scaring away potential international investors. Our negative news parameter envelopes political clashes, and inter-and intra-ethnic fighting in the case of Ghana, and for Nigeria, in addition to the factors enumerated for Ghana, we include religious violence and clashes between government security operatives and restive Niger delta militants. The selection of these factors that make up the negative news parameter is justified on the grounds that the issues identified, if not well managed can potentially destabilise the two countries.

Our empirical findings indicate that in the first moment, there is a bi-directional relationship between the equity and foreign exchange markets of Ghana. For Nigeria, we find that current return in the equity market is influenced by previous returns in the foreign exchange market. For volatility spillover, we find previous volatility in the equity market of Ghana influencing the current volatility in the foreign exchange market. We also find that political related violence negative news affects the two markets of Nigeria, but for Ghana it only affects the equity market. Moreover, ethnic violence related negative news affects respectively the returns of the equity and the foreign exchange markets of Ghana and Nigeria. Only the volatility in the foreign exchange market of Ghana is sensitive to political violence related news. We find volatility persistence in all the markets of both countries with the equity market of Ghana exhibiting volatility asymmetry.

The findings from this study add to the empirical literature on the linkages between the equity and currency markets, the risk-return performance of international equity and currency markets, and the impact of news on financial markets. In particular, European and American investors flocking to Africa will better appreciate the potential portfolio diversification implications of investing in the financial markets of Ghana and Nigeria, and the varied impact of news associated with political clashes, and inter-and intra-ethnic conflicts, religious violence and clashes between government security operatives and restive Niger delta militants.

The rest of this paper is organised as follows. Section Two presents key stylised facts of the countries studied, the model of analysis is presented in Section Three, Section Four reviews the data, Section Five presents and discusses the empirical findings and, lastly, Section Six captures the conclusion.

2 SOME FACTS ON THE COUNTRIES STUDIED

On the foreign exchange front, Ghana fully liberalised its foreign exchange market in 1988 after undergoing significant changes since independence from Great Britain in 1957. The liberalization gave birth to a floating exchange rate regime. The floating exchange regime allowed private individuals to join the banks by operating a Foreign Exchange Bureau, thereby eliminating the parallel black market that existed for foreign currency exchange. The Foreign Exchange Bureau operators were given the mandate to freely determine their sale and purchase prices in the major currencies, and the public could freely buy or sell any of these foreign currencies from and to them. Nigeria, on the other hand, adopted a regime of managed float since 1986. The regime of managed float gave the government the right to intervene in the foreign exchange market. The government can influence the exchange rate but does not commit itself to maintaining a fixed exchange rate or some narrow limits around it.

The Ghana and Nigeria equity markets have enjoyed mixed performance[10] in recent times; for instance, the year-to-year total index gain was 74.73% for Nigeria in 2007 and 58.08% for Ghana in 2008. In 2009, during the peak of the global recession, investors on both exchanges sought refuge in short-term securities; they shunned asset considered risky. Hence, the equity markets in Ghana and Nigeria recorded -56.58% and -33.80% respectively. The real gross domestic product (GDP)[11] for Ghana and Nigeria was 3.5% and 5.6% respectively in 2009, and it increased to 5.7% and 8.4% in 2010 respectively. Clearly the stock market is undoubtedly poised to recover. With Ghana joining oil producing countries in the last quarter of 2010, the real GDP was 13.6% in 2011 and that of Nigeria for the same year was 7.2%. Ghana's new found wealth from crude oil production will significantly reduce the need for outside financial assistance, increasing international confidence in its financial assets and potentially attract more international foreign private investors to the country's markets and industries. This is especially so given that 2010 and 2011 have been Europe's age of austerity contagion. Numerous austerity measures have been imposed by various European governments aimed at reining in the downward spiral of the euro and stabilising the European and world equity markets. Economists predict that the austerity measures will stifle the fragile recovery from the 2008 financial crisis. Estimates by the International Monetary Fund, for instance, show that accumulated real GDP growth for European economies was 1.7% in 2010 and 1.7% in 2011, compared with 5.0% and 5.5% respectively for the same period for the Sub-Saharan African economies.

The descriptive data on the equity markets of Ghana and Nigeria is presented in Table 1 in Appendix A. It can be inferred from Table 1 that trading volume was low in both countries. This may be attributed to the 2008-2009 global recession. In 2008, for instance, when the global financial crisis was severe in advanced markets, African

[10] The equity market performance figures were taken from the African Securities Exchanges Association Year books located at http://www.africansea.org/asea/library.aspx.
[11] The GDP figures were culled from IMF World Economic Outlook Publication, April 2011, located at http://www.imf.org/external/pubs/ft/weo/2011/01/pdf/text.pdf

markets were spared. The effects took a strangle hold on African financial markets in 2009. Thus, the volume traded on the Ghana equity market increased from 287.22 million in 2007 to 546 million in 2008 but fell to 97 million in 2009. For Nigeria, it increased from 138.1 billion in 2007 to 193.14 billion in 2008 but fell to 102.85 billion in 2009. It can be gained said that, although the volume traded on the Nigeria equity market increased in 2008 in comparison to 2007, the market index performance for 2008 was -45.8% and that of Ghana was 58.1%. This is because the Nigeria economy relies heavily on the export of crude oil (the oil component is about 95% of total exports[12]), which experienced low world demand during the latter part of 2008 and with the equity market dominated by companies in the crude oil business, investors sought refuge in short-term less risky investments; hence, the negative growth. For Ghana, however, the positive performance may be due to the rise in the price of gold, as corroborated by Osei (2006), who found that an upward movement in the world price of gold, which is a major mineral export of Ghana, increases the demand for shares. The turnover ratios for both countries, which is less than 20%, shows that the two markets are grappling with low liquidity as a consequence of the prevalence of thin trading and to draw any meaningful conclusion from empirical work on these two markets, thin trading should be taken into account.

On the issue of conflicts, the root causes in Ghana and Nigeria in particular, and Africa in general, can be deemed idiosyncratic in nature. The root causes can partly be traced to the balkanization of the continent; as a result, divided homogenous ethnic groups and tribes found themselves in different countries where they have to co-exist and compete with other tribes for a share of the dwindling natural resources. The competition erupts in violence and, as people migrate in search of fertile arable land, water and other resources elsewhere, the violence exacerbates. Also, the tribal head or chieftaincy installation has been the source of most intra-tribal or ethnic conflicts. The British colonialists added much clout to the chieftaincy institution in Ghana and Nigeria when they adopted the indirect rule system. The British governed the indigenes through their chiefs. After independence, the institution became so powerful and, because of the numerous tribes and ethnic groups found in Ghana and Nigeria, the national interest is usually subordinated to an unquestionable allegiance to an ethnic group or tribe to which one belongs. Politicians have exploited these by forming alliances with chiefs, thereby politicising the tribal head or chieftaincy installation

[12] Culled from “Nigeria economy picks up on non-oil sector growth” http://af.reuters.com/article/investingNews/idAFJOE82C02Z20120313

process without regard to the resulting violence. Thus, the causes of violence in Ghana can be summed as the right to control resources and power. The same can be said of Nigeria with religious overtones.

3 METHODOLOGY

3.1 Thin Trading Adjustment

Daily returns for each series are computed by taking the first difference of the natural logarithm of total return index and exchange rate multiplied by 100 respectively for the equity market indices and the exchange rate series. Thus,

$$r_t = \ln\left(I_t/I_{t-1}\right) * 100, \tag{1}$$

where I_t and I_{t-1} represent the current days close and the previous day close respectively. The assumption underlying the logarithmic procedure is that stock returns are log-normal and continuously traded. In the presence of thin trading, this assumption will not hold.

Studies by Scholes and Williams (1977), Dimson (1979), Fowler and Rorke (1983) and Lo and MacKinlay (1990) have come to a consensus that thin trading introduces a potentially serious econometric problem of errors in variables, and conclusions drawn from empirical work may be misleading. Moreover, Appiah-Kusi and Menya (2003), and Mlambo and Biekpe (2005) have documented pervasive thin trading on the equity markets of Ghana and Nigeria. Thin or infrequent trading occurs when stocks do not trade consecutively. This can potentially lead to spurious autocorrelation in the return series.

Cohen, Hawawini, Schwartz, and Whitcomb (1983) and Miller, Muthuswamy and Whaley (1994) are among the number of studies that have proposed methods for adjusting for thin trading. McInish and Wood (1986) argue that the Cohen et al. (1983) methodology provides a slight reduction in the magnitude of bias in beta estimates. The Miller et al. (1994) model, followed by Appiah-Kusi and Menya (2003), Al-Khazali, Ding and Pyun (2007) and Rayhorn, Hassan, Yu and Janson (2007) is, however, adopted for this study. The model uses a moving average that reflects the number of non-trading days to remove the effect of thin trading and calculates returns adjusted for the effect of non-trading. Miller et al. (1994)[13] have shown that the non-trading adjustment is equivalent to estimating an AR(1) model. Thus,

$$r_t = \alpha + \beta r_{t-1} + \varepsilon_t. \tag{2}$$

Using the residuals (ε_t) from Equation (2), the adjusted returns are estimated as follows:

$$r_t^{adj} = \varepsilon_t/(1-\beta), \tag{3}$$

where r_t^{adj} is the return at time t adjusted for thin trading and assumes that the non-trading adjustment required to correct return is constant over time. Antoniou, Ergul and Holmes (1997), however, argue that this assumption may hold for highly liquid stock and for Ghana and Nigeria equity markets where illiquidity and thin trading is pronounced, adjustment is more likely to be time dependent. Hence, we employ the recursive least squares estimation technique in estimating Equation (2).

3.2 Bivariate VAR-EGARCH Model with a Dummy Variable

Engle (1982) pioneered the use of the Autoregressive Conditional Heteroskedasticity (ARCH) model for capturing volatility clustering in financial data. Due to the limitless number of lags associated with the ARCH model, Bollerslev (1986) introduced the generalised ARCH model (GARCH) which imposes a non-negativity constraint on the estimated parameters. The inability of the ARCH and GARCH models to capture the leverage effect, which is usually present in stock market prices, Nelson (1991) introduced the exponential GARCH (EGARCH) model. This model allows for the modelling of price movements that are negatively correlated with volatility. It also allows for the assessment of whether shocks to conditional variance are persistent and

[13] See Miller et al. (1994) for proof

imposes no restriction on the parameters to ensure non negativity of the conditional variance (see Bollerslev, Chou and Kroner, 1992, for a review of the ARCH family models).

To capture the simultaneous effects of return and volatility spillovers between the equity and the currency markets, a Bivariate VAR-EGARCH model is used. This allows us to model short-run dynamic relationships, long memory and co-movements in volatility between the equity and the foreign exchange markets. We include a binary variable to cater for the reaction of the markets to negative news. Using the return, $r_{i,t}^{adj}$, where i = 1, 2 (1 = equity market and 2 = foreign exchange market) and the dummy denotes political violence, and inter and intra ethnic conflicts news for Ghana. For Nigeria, in addition to the events enumerated for Ghana, we include news related to religious violence and clashes between government security operatives and Niger delta militants. We, therefore, set up the Bivariate VAR-EGARCH model with a dummy variable where the dummies are inserted in turns as follows:

$$r_{i,t}^{adj} = \beta_{i0} + \sum_{j=1}^{2} \beta_{ij} r_{j,t-1}^{adj} + \varphi_i Dummy_t + \varepsilon_{i,t,} \quad \text{for } i,j = 1, 2 \text{ and } i \neq j, \qquad (4)$$

$$\sigma_{i,t}^2 = exp\left[\alpha_{i,0} + \sum_{j=1}^{2} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2) + \phi_i Dummy_t\right], \qquad (5)$$

$$\text{for } i,j = 1, 2 \text{ and } i \neq j.$$

The VAR model to capture the short-run dynamic relationships between the stock returns and the exchange rate is represented by Equation (4). In this model, the conditional mean in each market is a function of past own returns, cross market past returns and negative news sensitivity. The term β_{i0} represents the long-term drift coefficients and the lead-lag relationships are captured by coefficients β_{ij} for i, j = 1, 2 and $i \neq j$. A statistically significant β_{ij} would imply that current returns in market j could be used to predict future returns in market i. Similarly, a statistically significant φ_i would imply that returns in market i are sensitive to negative news.

Equation (5) is the conditional variance equation which allows own standardised as well as cross standardised innovations from the other market to exert asymmetric impact on the volatility. If $\alpha_{i,j}$, for i, j = 1, 2 and $i \neq j$ is significantly different from zero, then volatility of market j will spill over to market i. The coefficient ϕ_i captures market i's volatility sensitivity to negative news. The functional f_j is an asymmetric function of past standardised innovations. Current innovations are given as $z_{i,t} = \varepsilon_{i,t}/\sigma_{i,t}$. The sign and size effect of the lagged innovations is captured by the following function:

$$f_j(z_{j,t-1}) = \left(|z_{j,t-1}| - E|z_{j,t-1}| + \delta_j z_{j,t-1}\right). \tag{6}$$

In Equation (6), the size effect is measured by the first two terms and third term captures the sign effect. The parameter δ_j measures the asymmetric impact on the volatility of market i with the following partial derivatives:

$$\partial f_j(z_{j,t}) \,/\partial\, z_{j,t} = \begin{pmatrix} 1+\delta_j, \text{ for } z_j > 0 \\ -1+\delta_j, \text{ for } z_j < 0 \end{pmatrix}. \tag{7}$$

Asymmetry exists if the coefficient δ_j is negative and statistically significant for market j. Thus a stock market decline in market j $(z_{j,t-1} < 0)$ will be followed by higher volatility than stock market advances $(z_{j,t-1} > 0)$. This phenomenon will be consistent with the leverage effect, whereby a market decline produces a higher aggregate debt to equity ratio and, hence higher, volatility (Koutmos, 1996), or the risk premium effect where news of increasing volatility causes risk-averse investors to reduce the demand for a stock. A statistically significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovation in market j increases volatility in market i more than a positive innovation of an equal magnitude. The number of times that negative innovations increase volatility more than positive innovations in market j is defined as $|-1+\delta_j|/(1+\delta_j)$. Persistence of volatility is measured by γ_i in Equation (5) and the time period required for shocks to decrease to one half of the original size in market i is quantified by the half-life (HL) given as

$$\text{HL} = \frac{\ln(0.5)}{\ln|\gamma_i|}. \tag{8}$$

Finally, the residuals from Equation (4) are assumed to be normal and the conditional covariance specification is the product of the standard deviations as described by the following equations:

$$\varepsilon_{i,j}|X_{t-1}{\sim}N(0,H_t|I_{t-1}),\quad H_t\equiv\begin{bmatrix}\sigma_{1.t}^2 & \sigma_{12.t}^2\\ \sigma_{21.t}^2 & \sigma_{2.t}^2\end{bmatrix}\quad \text{for } i,j=1,2 \text{ and } i\neq j, \tag{9}$$

$$\sigma_{i,j,t}=\rho_{i,j}\sigma_{i,t}\sigma_{j,t}\qquad \text{for } i,j=1,2 \text{ and } i\neq j, \tag{10}$$

where X_{t-1} is the information set at time t-1 and H_t is the conditional variance-covariance matrix at time t. Equation (10) captures the contemporaneous relationships between the returns of the two markets and correlation is assumed to be constant in this model. This specification parameterises the conditional covariance, and it implies that the correlation of the return of market i and j is constant and this assumption assures a positive semi-definite variance-covariance matrix. This reduces the number of parameters to be estimated in the model to twenty-one, and with the assumption of normality and a sample of $\mathcal{T}$ observations, the log-likelihood function for the VAR-EGARCH model can be written as

$$L(\Theta)=-0.5(\mathcal{N}\mathcal{T})ln2\pi-0.5\sum_{t=1}^{T}(ln|S_t|+\varepsilon_t'S_t^{-1}\varepsilon_t), \tag{11}$$

where $\mathcal{N}$ is the number of the two equations and Θ, the 21 x 1 parameter vector to be estimated. $\varepsilon_t'=[\varepsilon_{1,t,}\varepsilon_{2,t}]$ is the 1 x 2 vector of innovations at time t, S_t the 2 x 2 time varying conditional variance-covariance matrix with diagonal elements given by Equation (5) for $i,j=1,2$ and $i\neq j$. The log likelihood function is highly nonlinear in $L\Theta$; we, therefore, use the Broyden, Fletcher, Goldfarb and Shanno (BFGS) algorithm (in RATS ™ 7.3) to maximise $L(\Theta)$, via Quasi-Maximum Likelihood Estimation (QMLE) which is robust to the distribution of the disturbance term. Bollerslev and Wooldridge (1992) have shown that, under a correct specification of the conditional mean and variance, consistent estimates of the parameters could be obtained via QMLE.

4 DATA

The data set consists of daily closing exchange rates and total equity market indices for Ghana and Nigeria. The equity market indices are the S&P Ghana BMI price index and the S&P Nigeria BMI price index, and for exchange-rate series, we use the exchange rate of the dollar per local currency as a proxy for the exchange rate market. Thus, Cedi/Dollar and Naira/Dollar for Ghana and Nigeria respectively were obtained from Datastream. The sample period for Ghana runs from 1st August, 2005, to 30th April, 2010, yielding 1,240 observations and that of Nigeria from 1st August, 2000, to 30th April, 2010, yielding 2,544 observations. The raison d'être for the starting date for Ghana is that trading on the Ghana stock exchange was switched from three days a week to five days a week from 1st August, 2005. We define our negative news binary variables as news that has the potential to weaken the security and plunge the country in question into violence, thereby scaring away individual and institutional investors. The negative news variables, which were obtained using Google News Archive, encompasses political clashes, especially in the run up to elections, inter and intra ethnic fighting in the case of Ghana, and for Nigeria, in addition to the factors enumerated for Ghana above, we include religious violence and clashes between government security operatives and the restive Niger delta militants. Totally, we have 22 and 48 political clashes, and intra and inter-ethnic conflicts dummy events respectively for Ghana, and for Nigeria, we have 37, 36, 57 and 42 dummy events for political clashes, inter-and intra-ethnic conflicts, religious violence, and clashes between government security operatives and restive Niger delta militants respectively over the respective sample periods.

Given the purpose of this paper and the fluidity of information, tick data will be ideal to measure the impact of news on the equity and foreign exchange markets. The non-existence of tick data on these equity markets makes using daily data the ideal compromise. Weekly or monthly return horizon may be too long a time span and cannot mirror the impact of news on the equity returns and exchange rate returns series.

The modelling methodology demands that the series including the adjusted returns, are stationary at level. Predictably, the augmented Dickey-Fuller (1979) test rejects the null of nonstationarity for all four return series used for the study.

Table 2. Summary Statistics and Correlation Matrix

Panel A: Summary Statistics

	Ghana		Nigeria	
		Currency		Currency
Statistic	Equity	Cedi/Dollar	Equity	Naira/Dollar
Mean	0.016	0.036	-0.033	0.014
Median	0.004	<0.001	-0.065	<0.001
Std. Dev.	1.137	0.505	2.078	0.637
Skewness	0.205	1.316	-0.136	2.536
Kurtosis	14.445	20.758	9.989	86.763
Jarque-Bera	6776.42**	16637.70**	5184.96**	746439.90**
LB(12)for r_t	35.530**	78.667**	42.299**	67.802**
LB(12) for r_t^2	28.815**	183.950**	387.550**	230.700**
Arch (p)	0.453**	0.789**	0.214**	0.069**
ADF	-33.253**	-33.651**	-32.326**	-33.188**

Panel B: Unconditional Correlations

Ghana		Nigeria	
	Cedi/Dollar		Naira/Dollar
Equity	-0.445**	Equity	-0.509**
	(-15.672)		(-25.657)

**denotes statistically significant at 5%, and numbers in parenthesis are t-statistics. Arch (p) is the Engle (1982) test for ARCH up to lag order 1, LB(12) is Ljung–Box Q-statistic at lag 12 and ADF denotes Augmented Dickey Fuller unit root test

Panel A of Table 2 shows the summary statistics for the return series for the equity and foreign exchange markets of Ghana and Nigeria. The mean for all the markets is positive, except for the equity market of Nigeria. This may be due to the string of negative performances by the Nigerian capital market. For instance, the Nigerian All Share index, which is a proxy for the total market performance, had a year to year gain of -45.8% and -33.8% for 2008 and 2009 respectively. These may be the result of the global financial meltdown in the latter part of 2008 through 2009 where investors turned to less risky short-term investments. In particular, the time series graphs depicted in Figures 1a to 1e and 2a to 2e respectively show the effect of the global financial crisis on the equity and the currency markets of Ghana and Nigeria. Also, the

Nigerian stock market lost about 70 % of its value during the peak of the financial crisis. However, all the markets exhibit positive standard deviations. Positive shocks are more common in the markets, except in the Nigerian equity market which exhibits negative skewness.

The equity markets in both countries exhibit higher leptokurtic behaviour and the Jacque-Bera statistics decisively reject the normality assumption associated with return distribution for all markets. The rejection of non-normality is inconsistent with a linear model, and this re-enforces our motivation for using a nonlinear modelling methodology. The Ljung-Box (LB) statistics show evidence of serial dependence in the return and squared return series. The ARCH test of Engle (1982) which is χ^2 distributed also shows the presence of conditional heteroskedasticity in all the series. A simple *t*-test of the unconditional correlation in Table 2 Panel B shows that the unconditional correlations between the equity and the foreign exchange markets of both countries are negative and statistically significant.

White noise and white chaos cannot be distinguished by the Ljung-Box statistical tests. To differentiate between the white noise and white chaos, which will help in identifying the type of the nonlinear structure, and, hence, improve the formulation of the model, we perform the BDS test of Brock, Dechert and Scheinkman (1996). The BDS test even becomes more compelling given the thin trading adjustments we made to the data. The test is based on the null hypothesis of independent and identically distributed (IID) and tests for the presence of nonlinear dependence in the returns series. The BDS test results, with epsilon values ranging from half to two times the standard deviation for 2 to 6 correlation dimension shown in Table 3, confirm the presence of chaotic innovations in the series for all the markets, hence a nonlinear dependence can be inferred.

Table 3. BDS Test for Nonlinearity

Correlation Dimension	Ghana Equity	Ghana Cedi/Dollar	Nigeria Equity	Nigeria Naira/Dollar
2	0.020**	0.039**	0.024**	0.043**
	(8.068)	(10.831)	(15.582)	(15.724)
3	0.029**	0.068**	0.030**	0.095**
	(10.283)	(13.651)	(19.384)	(20.763)
4	0.0315**	0.079**	0.028**	0.133**
	(13.834)	(15.454)	(22.654)	(23.051)
5	0.028**	0.076**	0.022**	0.161*
	(15.832)	(16.754)	(26.083)	(25.334)
6	0.024***	0.070**	0.016**	0.177**
	(19.923)	(18.014)	(30.812)	(27.622)

**denotes statistically significant at 5%, and numbers in parenthesis are *z*-statistics

Engle and Ng (1993) propose a formal test for the asymmetric response of variance to past shocks. This test considers two sources of asymmetric response to the variance. Thus, the sign effect, that is past shocks of different signs have different effect on the present volatility and the size effect, where past shocks of the same sign but different magnitude have different effects on the present volatility. In this study, we estimate a symmetric GARCH (1,1) model in the first stage and use the standardised residuals defined as $\hat{z}_t = (\hat{\varepsilon}_t/\hat{\sigma}_t)$, where $\hat{z}_t$ and $\hat{\sigma}_t$ are the estimated residuals and standard deviation of the series respectively. We estimate the following regression to test whether asymmetric effects are present in the squared standardised residuals. Thus,

$$\hat{z}_t = \phi_0 + \phi_1 s_{t-1}^{-} + u_t, \tag{12}$$

$$\hat{z}_t = \phi_0 + \phi_1 s_{t-1}^{-} \varepsilon_{t-1} + u_{t,} \tag{13}$$

$$\hat{z}_t = \phi_0 + \phi_1 s_{t-1}^{+} \varepsilon_{t-1} + u_t, \tag{14}$$

where u_t is the normally distributed error term, s_{t-1}^{-} is the dummy variable and takes the value of 1 if $\hat{\varepsilon}_{t-1}$ is negative and zero otherwise. A statistically significant ϕ_1 in Equation (12) will imply that positive and negative shocks to $\hat{\varepsilon}_{t-1}$ impact differently on the conditional variance. Similarly, a statistically significant ϕ_1 in Equations (13) and (14) suggest the presence of negative size bias and positive size bias respectively.

Additionally, Engle and Ng (1993) propose a joint test for sign and size bias with a Lagrange multiplier test with χ^2 distribution. The statistics are obtained by multiplying the number of observations by the R^2 of the regression of the squared standardised residuals on the three independent variables used in Equations (12), (13) and (14). The regression is thus,

$$\hat{z}_t = \phi_0 + \phi_1 s_{t-1}^{-} + \phi_2 s_{t-1}^{-} \varepsilon_{t-1} + \phi_3 s_{t-1}^{+} \varepsilon_{t-1} + u_t. \tag{15}$$

The results of these diagnostic tests for the GARCH (1,1) model are presented in Table 4.

Table 4. Volatility Specification Test

	Ghana		Nigeria	
Statistic	Equity	Cedi/Dollar	Equity	Naira/Dollar
Size bias	0.667	-0.248	-0.007	0.912
	(0.786)	(-0103)	(-0.064)	(0.625)
Positive Sign bias	0.087	0.990**	0.199**	0.583**
	(0.564)	(4.081)	(4.142)	(11.591)
Negative Sign bias	-0.721**	-0.999**	-0.403**	-0.600**
	(-4.824)	(-5.413)	(-8.644)	(-8.164)
Joint test	0.559	30.688**	45.237**	69.686**

**denotes statistically significant at 5%, and numbers in parenthesis are *t*-statistics

It can be seen in Table 4 that the variance of return is larger after a positive shock for the foreign exchange market of Ghana and for the equity and foreign exchange markets of Nigeria. Thus, innovations in these markets may have an additional effect on their volatility beyond what is predicted by the symmetric model. Also, negative shocks, large and small, have different effects on the standardised residuals for all the markets of both countries. The source of these effects, however, cannot be determined since they are caused by both positive and negative innovations. Finally, the joint test is significant for the foreign exchange market of Ghana and the equity and foreign exchange markets of Nigeria. Overall, an asymmetric effect on volatility exists in all the markets and to eliminate bias in this empirical work and to assure consistent estimates, we apply a Bivariate VAR-EGARCH model which allows us to simultaneously examine the first and second moment dynamics in the foreign exchange and equity markets.

5 EMPIRICAL FINDINGS

The quasi-maximum likelihood estimates of the Bivariate VAR-EGARCH model are reported in Table 5. Focusing on the parameters that describe the conditional mean in each market, it can be seen that there are bidirectional lead-lag relationships between the equity and foreign exchange markets for Ghana. Thus, current returns in the equity market are positively correlated with past returns in the foreign exchange market and current returns in the foreign exchange markets are negatively correlated with past returns in the equity market. For Nigeria, on the other hand, current returns in the equity market positively correlate with past returns in the foreign exchange market and not vice versa.

Economically, depreciation in the local currency, for instance, will drag down the equity market, and inflation which is the result of currency depreciation may stifle the volume and value of stock traded on the equity market. This is because international investors may decide to reduce their portfolio of domestic investments. This may depress the domestic equity market in the short run.

In the second moment dynamics, there exists unidirectional volatility spillover for both countries. Thus, for Ghana, current volatility in the foreign exchange market contains some amount of past innovations from the equity market, whereas for Nigeria, past innovations from the foreign exchange market influence current volatility in the equity market. We have to concede that changes in the equity market may not be entirely the results of innovations from the currency market and vice versa. Investor sentiment in relation to risk and return may also cause current returns in either the currency or equity market to change.

Table 5. Quasi-Maximum Likelihood Estimates of the Bivariate VAR-EGARCH Model

$$r_{i,t}^{adj} = \beta_{i0} + \sum_{j=1}^{2} \beta_{ij} r_{j,t-1}^{adj} + \varphi_i Dummy_t + \varepsilon_{i,t,} \quad \text{for i, j = 1, 2 and } i \neq j,$$

$$\sigma_{i,t}^{2} = exp\left[\alpha_{i,0} + \sum_{j=1}^{2} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^{2}) + \phi_i Dummy_t\right],$$

$$\text{for i, j = 1, 2 and } i \neq j.$$

$$f_j(z_{j,t-1}) = \left(\left|z_{j,t-1}\right| - E\left|z_{j,t-1}\right| + \delta_j z_{j,t-1}\right).$$

Ghana Equity		Cedi/ Dollar		Nigeria Equity		Naira/ Dollar	
$\beta_{1,0}$	0.020**	$\beta_{2,0}$	0.024**	$\beta_{1,0}$	-0.077**	$\beta_{2,0}$	0.010
	(63.597)		(4.382)		(-1.990)		(1.896)
$\beta_{1,1}$	0.185**	$\beta_{2,1}$	-0.025**	$\beta_{1,1}$	0.167**	$\beta_{2,1}$	0.004
	(5.0712)		(-4.0343)		(5.3343)		(0.7593)
$\beta_{1,2}$	0.507**	$\beta_{2,2}$	-0.409**	$\beta_{1,2}$	0.973**	$\beta_{2,2}$	-0.224**
	(17.336)		(-16.265)		(8.234)		(-5.703)
φ_1^P	0.457**	φ_2^P	0.002	φ_1^P	0.490**	φ_2^P	-0.062**
	(2.515)		(0.056)		(13.689)		(-2.220)
φ_1^E	-0.118**	φ_2^E	-0.019	φ_1^E	-0.302	φ_2^E	0.060**
	(-3.548)		(-0.656)		(-1.434)		(2.980)
				φ_1^R	-0.108	φ_2^R	-0.041
					(-0.403)		(-0.867)
				φ_1^M	0.780	φ_2^M	-0.086
					(0.217)		(-0.791)
$\alpha_{1,0}$	0.024	$\alpha_{2,0}$	-0.008	$\alpha_{1,0}$	0.1.26**	$\alpha_{2,0}$	0.223
	(1.458)		(-0.479)		(3.684)		(1.058)
$\alpha_{1,1}$	0.176**	$\alpha_{2,1}$	0.056**	$\alpha_{1,1}$	0.351**	$\alpha_{2,1}$	0.006
	(2.376)		(2.101)		(5.057)		(0.051)
$\alpha_{1,2}$	0.051	$\alpha_{2,2}$	0.194**	$\alpha_{1,2}$	0.049**	$\alpha_{2,2}$	0.377**
	(0.597)		(7.940)		(2.077)		(6.799)
ϕ_1^P	0.085	ϕ_2^P	-0.343**	ϕ_1^P	0.117	ϕ_2^P	0.116
	(0.666)		(-4.267)		(0.649)		(0.610)
ϕ_1^E	-0.004	ϕ_2^E	-0.077	ϕ_1^E	0.001	ϕ_2^E	-0.279
	(-0.048)		(-1.479)		(0.010)		(-0.783)
				ϕ_1^R	-0.043	ϕ_2^R	0.101
					(-0.196)		(0.352)
				ϕ_1^M	0.0203	ϕ_2^M	-0.433
					(0.070)		(-0.153)
δ_1	-0.722**	δ_2	0.039	δ_1	0.020	δ_2	0.227
	(-3.524)		(0.356)		(0.390)		(1.920)
γ_1	0.945**	γ_2	0.983**	γ_1	0.920**	γ_2	0.968**
	(38.703)		(124.243)		(37.315)		(84.047)

** denote statistically significant at 5%. Numbers in parenthesis are *t*-statistics. The superscripts *P, E, R* and *M* denote negative news related to political, ethnic, religious and military clashes with oil militants in the restive Niger Delta region respectively.

Interestingly, negative news emanating from political clashes and ethnic violence affects the returns on the Ghana equity market, and, for Nigeria, the former affect the returns of the equity and foreign exchange markets, whereas the latter only affect the returns of the equity market. We found no evidence of depressing news emanating from religious violence and military clashes with the restive Niger delta oil militants affecting the returns of the equity and foreign exchange markets of Nigeria.

In the second moment, only the volatility in the foreign exchange market of Ghana is influenced by political violence related negative news. For Nigeria, on the other hand, there is no evidence of negative news from political conflicts, ethnic violence, religious clashes and military operations against Niger delta oil militants influencing the volatility of the equity and foreign exchange markets. Given the brutal spasms of religious and ethnic clashes in recent times in Nigeria, it is surprising that volatility in the equity and foreign exchange markets are unaffected by these upheavals. This may be due to the confidence investors repose in the structures put in place to address these disturbances. The same reason can be tendered for Ghana, except for the volatility of the foreign exchange market, which is sensitive to political violence related news. This phenomenon may be explained by, unlike Nigeria, which earns a significant amount of foreign currency from crude oil exports, which has an inelastic foreign demand and, therefore, can weather any international sanctions which may be imposed as a response to any unconstitutional change in government. Ghana, on the other hand, does not have that luxury and any response from the international community to any unconstitutional political changes will invariably affect the macroeconomic fundamentals. This makes players in the foreign exchange market sensitive to any political negative news in comparison to ethnic violence news.

We find that the asymmetric coefficient, $\delta_{i,t}$ is negative and statistically significant for the equity market of Ghana. Thus, stock market declines will be followed by higher volatility than stock market advances. Also, negative innovation in the equity market increases volatility in the foreign exchange market more than a positive innovation of an equal magnitude. The volatility persistent parameter, $\gamma_{i,t}$, is statistically significant in all the markets for both countries. The time period required for shocks to decrease to one half of the original size, defined as $\ln(0.5)/\ln|\gamma_i|$, is approximately 12 and 40 days for the equity and the foreign exchange markets respectively for Ghana, and, for Nigeria, it takes approximately 8 and 21 days for the equity and foreign exchange markets respectively. The extent to which negative innovations increase volatility more than positive innovation, defined as $|-1 + \delta_j|/(1 + \delta_j)$, is about 2.60 for the Ghana equity market. This means that, for the Ghana equity market, negative innovations of stock prices have impact on volatility a little over two and a half times larger than positive innovations. Since the asymmetric parameter, $\delta_{i,t}$ is not significant for the foreign exchange market of Ghana, and the equity and foreign exchange markets of Nigeria, there is no difference between the impact of negative and positive innovations in those markets.

Residual based diagnostic tests in Table 6 show that the Bivariate VAR-EGARCH model with a binary variable satisfactorily explains the interactions between the variables in the two markets for both countries. Panel A shows that the estimated mean and the variance of the cross product of the standardised residuals are approximately equal zero and one respectively. The Ljung-Box statistics up to 12 lags show no evidence of serial correlation in the standardised residuals and squared standardised residuals at 5% level of significant. Thus, the noise terms are random and the assumption of constant correlation is justified. Also, the volatility specification test based on the news impact curve in Panel B of Table 6 shows no evidence of sign bias in the standardised residuals. The estimated conditional pairwise correlations of the standardised residuals shown in Panel C of Table 6 are considerably lower than the unconditional correlation estimates reported in Panel B of Table 2. A simple t-test suggests that the difference is statistically significant. Intuitively, failure to account for heteroskedasticity will bias the correlation estimates upwards, overstate the degree of connectedness between the two markets and reduce the scope of diversification. With the negative correlation and given the risk-expected return efficient frontier, risk averse investors in the equity markets of Ghana and Nigeria would be better off by including investments in the currencies of these two countries in their portfolio mix.

Clearly, without the effect of the thin trading adjustment, the unconditional correlations between the returns and the adjusted returns of the equity markets of Ghana and Nigeria should be equal to one. As Panel D of Table 6 shows, the unconditional correlation coefficients between the returns and the adjusted returns for the equity markets of both countries are less than one and significant albeit marginal in absolute terms.

Table 6. Robustness Tests

Panel A: Model Diagnostics

	Ghana Equity	Cedi/Dollar	Nigeria Equity	Naira/Dollar
Mean	-0.010	0.023	0.027	-0.041
Variance	1.003	0.994	0.999	1.000
LB[12] for $Z_{i,t}$	25.208	57.268	33.247	19.444
LB[12] for $Z_{i,t}^2$	16.226	16.226	13.129	13.129

Panel B: Volatility Specification Test Based on the News Impact Curve

	Ghana Equity	Cedi/Dollar	Nigeria Equity	Naira/Dollar
Sign Bias	-0.103	0.001	-0.035	0.294
	(-0.700)	(0.071)	(-0.148)	(1.232)
Negative Size bias	0.034	-0.535	-0.049	-0.473
	(0.341)	(-1.412)	(-0.487)	(-1.639)
Positive Size bias	0.062	0.001	0.028	-0.091
	(0.599)	(0.003)	(0.285)	(-0.336)
Joint Test	0.191	1.720	0.182	1.133

Panel C: Conditional Correlation of Standardised Residuals

	Ghana Equity	Cedi/Dollar		Nigeria Equity	Naira/Dollar
Equity		-0.351**	Equity		-0.367**
		(-14.618)			(-15.343)

Panel D: Unconditional Correlation between the Returns and Adjusted Returns

	Ghana Return	Adjusted Return		Nigeria Return	Adjusted Return
Return		0.979**	Return		0.953**
		(34.481)			(48.078)
Adjusted Return	0.979**		Adjusted Return	0.953**	
	(34.481)			(48.078)	

***denotes statistically significant at 5%. The numbers in parenthesis are *t*-statistics

Table 7. Quasi-Maximum Likelihood Estimates of the Bivariate VAR-EGARCH Model (Non-Adjusted Return Series)

$$\mathrm{r}_{i,t} = \beta_{\mathrm{i}0} + \textstyle\sum_{j=1}^{2} \beta_{ij}\mathrm{r}_{i,t-1} + \varphi_i Dummy_t + \varepsilon_{i,t,} \quad \text{for i, j = 1, 2 and } i \neq j,$$

$$\sigma_{i,t}^2 = exp\left[\alpha_{i,0} + \textstyle\sum_{j=1}^{2} \alpha_{i,j}\, f_j(z_{j,t-1}) + \gamma_i \ln\left(\sigma_{i,t-1}^2\right) + \phi_{\mathrm{i}} Dummy_t\right],$$

$$\text{for i, j = 1, 2 and } i \neq j.$$

$$f_j(z_{j,t-1}) = \left(|z_{j,t-1}| - E|z_{j,t-1}| + \delta_j z_{j,t-1}\right).$$

Ghana Equity		Cedi/ Dollar		Nigeria Equity		Naira/Dollar	
$\beta_{1,0}$	0.022** (9.420)	$\beta_{2,0}$	0.025** (32.748)	$\beta_{1,0}$	0.017 (0.698)	$\beta_{2,0}$	0.009 (1.637)
$\beta_{1,1}$	0.033** (11.362)	$\beta_{2,1}$	-0.021** (-23.893)	$\beta_{1,1}$	0.385** (16.777)	$\beta_{2,1}$	0.018** (3.777)
$\beta_{1,2}$	0.556** (7.932)	$\beta_{2,2}$	-0.416** (-15.091)	$\beta_{1,2}$	0.567** (9.888)	$\beta_{2,2}$	-0.195** (-5.806)
φ_1^P	0.407 (0.708)	φ_2^P	0.005 (0.034)	φ_1^P	0.154 (0.850)	φ_2^P	-0.023 (-0.485)
φ_1^E	-0.079 (-1.012)	φ_2^E	-0.0175 (-0.378)	φ_1^E	-0.152 (-1.390)	φ_2^E	0.043** (8.982)
				φ_1^R	-0.025 (-0.225)	φ_2^R	-0.055** (-9.982)
				φ_1^M	0.236 (0.084)	φ_2^M	-0.053 (-1.392)
$\alpha_{1,0}$	0.035 (1.077)	$\alpha_{2,0}$	-0.010 (-0.878)	$\alpha_{1,0}$	0.041** (4.518)	$\alpha_{2,0}$	0.027 (1.985)
$\alpha_{1,1}$	0.192 (1.837)	$\alpha_{2,1}$	0.040 (1.223)	$\alpha_{1,1}$	0.337** (7.908)	$\alpha_{2,1}$	-0.027 (-0.605)
$\alpha_{1,2}$	0.0461 (0.509)	$\alpha_{2,2}$	0.2069** (5.389)	$\alpha_{1,2}$	0.0369 (1.591)	$\alpha_{2,2}$	0.3674** (9.500)
ϕ_1^P	0.029 (1.193)	ϕ_2^P	-0.352 (-1.803)	ϕ_1^P	0.135 (0.842)	ϕ_2^P	0.392** (2.333)
ϕ_1^E	-0.027 (-0.124)	ϕ_2^E	-0.088 (-0.844)	ϕ_1^E	-0.008 (-0.071)	ϕ_2^E	-0.235 (-1.144)
				ϕ_1^R	-0.043 (-0.386)	ϕ_2^R	0.108 (0.775)
				ϕ_1^M	0.037 (0.329)	ϕ_2^M	-0.298 (-1.167)
δ_1	-0.502** (-2.930)	δ_2	0.048 (0.610)	δ_1	0.010 (0.217)	δ_2	0.224** (3.403)
γ_1	0.941** (22.677)	γ_2	0.983** (134.909)	γ_1	0.925** (66.750)	γ_2	0.976** (191.248)

** denote statistically significant at 5%. Numbers in parenthesis are *t*-statistics. The superscripts *P, E, R* and *M* denote negative news related to political, ethnic, religious and military clashes with oil militants in the restive Niger Delta region respectively.

To examine the effect of not adjusting for thin trading, we estimate the Bivariate VAR-EGARCH model on the non-adjusted returns series.

The robustness check in Panel A of Table 8 shows significant autocorrelations in the standardised residuals. Morever, the volatility specification test based on the news impact curve in Panel B of Table 8 shows significant negative size bias for the foreign exchange market of Ghana, thus rendering the estimates unreliable. Essentially, failure to adjust for the thin trading effect, although small in absolute terms, can introduce dependence into an otherwise random returns series (Lo and MacKinlay, 1990). For consistent and reliable estimates, thin trading should be adjusted to remove the potential bias from estimated standard errors when examining an equity market where there is thin trading.

Table 8. Robustness Tests (Non Adjusted Return Series)

Panel A: Model Diagnostics

	Ghana Equity	Cedi/Dollar	Nigeria Equity	Naira/Dollar
Mean	-0.028	0.028	0.014	-0.032
Variance	1.011	0.994	1.002	0.999
LB[12] for $Z_{i,t}$	20.894	55.961**	40.387**	32.130**
LB[12] for $Z_{i,t}^2$	16.996	16.994	13.129	12.773

Panel B: Volatility Specification Test Based on the News Impact Curve

	Ghana Equity	Cedi/Dollar	Nigeria Equity	Naira/Dollar
Sign Bias	-0.126	0.022	-0.037	0.2432
	(-0.871)	(0.151)	(-0.176)	(1.157)
Negative Size bias	0.053	-0.551**	-0.065	-0.348
	(0.528)	(-2.120)	(-0.488)	(-1.335)
Positive Size bias	0.096	-0.021	0.058	-0.099
	(0.963)	(-0.103)	(0.417)	(-0.455)
Joint Test,	0.382	1.769	0.220	0.818

Panel C: Conditional Correlation of Standardised Residuals

	Ghana Equity	Cedi/Dollar		Nigeria Equity	Naira/Dollar
Equity		-0.348**	Equity		-0.386**
		(-12.604)			(-17.932)
Cedi/Dollar	-0.348**		Naira/Dollar	-0.386**	
	(-12.604)			(-17.932)	

** denote statistically significant at 5%. Numbers in parenthesis are *t*-statistics.

6 CONCLUSION

This paper examined the lead/lag relationship and the volatility interactions between the equity and foreign exchange markets of Ghana and Nigeria. The sensitivity of the markets to negative news related to political violence, ethnic rivalries, religious violence and clashes between Nigeria's security forces and Niger Delta oil militants was also investigated. Unlike previous studies, which employed univariate GARCH and Granger models and did not take the thin trading characteristics of the equity markets into account, this study adjusts for thin trading and applied a Bivariave VAR-EGARCH model with a dummy variable to proxy for the negative news variables.

The empirical results show that for Ghana there is a bi-directional mean spillover between the equity and foreign exchange markets. Also, current volatility in the foreign exchange market was found to contain previous volatility from the equity market. Clearly, the second-moment results for Ghana show the activities of foreign investors; thus, any upturn or downturn on the equity markets is reflected in the currency market. The results also show that investors in the Ghana currency market are particularly sensitive to any dynamics on the equity market. For Nigeria, the mean spillover was from the foreign exchange market to the equity market, and volatility was not found to spillover to and from the two markets. The reason for the first moment unidirectional mean spillover from the currency market to the equity market of Nigeria may be due to crude oil being the chief foreign exchange earner[14]. The equity market tends to be sensitive to the dynamics of the currency market.

Additionally, the returns of the equity market in Ghana were found to be sensitive to political and ethnic violence related negative news. For Nigeria, political violence related negative news was found to influence the returns of both markets, with the returns in the foreign exchange market being sensitive to ethnic related violence negative news as well. Only the volatility in the foreign exchange market of Ghana was found to be sensitive to political violence related news. The results for Ghana and Nigeria are not surprising because political violence tends to propagate itself along ethnic fault lines. The findings also show significant volatility persistence in all the

[14] About 95% of Nigeria exports is compose of crude oil. This figure is culled from "Nigeria economy picks up on non-oil sector growth"
http://af.reuters.com/article/investingNews/idAFJOE82C02Z20120313

markets for both countries; thus, high volatility periods are apt to be followed by high volatility periods. Only the equity market of Ghana exhibits volatility asymmetry. We also find that thin trading affects the model estimation. When we adjusted for thin trading, the model performs better and we obtained reliable and consistent estimates.

Policy wise, the results may highlight the need for the two countries to take practical steps to reduce the incidence of violence in all forms in order to attract investors. Furthermore, to mitigate the bane of low liquidity on the stock exchanges, the two countries may use moral suasion and other fiscal incentives to encourage the numerous local and foreign-owned companies to list their shares on the exchanges. Finally, given the proximity and similar legal regimes, the two countries may consider merging the two equity markets. Moreover, in the meantime, the countries may encourage cross listing of shares by companies domiciled in any of the two countries with no subsidiary in the other country.

We concede that, due to the fluidity of information, daily closing equity price indices and currency exchange rates might not adequately capture the impact of negative news on the equity and foreign exchange markets of Ghana and Nigeria. Intraday data, when available, should be used to further explore the exact impact of negative news on the two markets of Ghana and Nigeria. Longer periods of data should be considered to side step the biases associated with using small samples, especially for Ghana. Finally, the Dynamic Equicorrelation model of Engle and Kelly (2009), which restricts the correlations in Equation (10) to be equal contemporaneously across all variables but not over time, should be considered as a candidate for the modelling methodology.

REFERENCES

Adjasi, C. K.D., and B.N. Biekpe, 2005, Stock Market Returns and Exchange Rate Dynamics in Selected African Countries: A Bivariate Analysis, *The African Finance Journal*, July, Cape Town, South Africa.

Adjasi, C. K. D., S. K. Harvey and D. Agyapong, 2008, Effect of Exchange Rate Volatility on the Ghana Stock Exchange, *African Journal of Accounting, Economics, Finance and Banking Research* 3(3).

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega, 2003, Micro Effects of Macro Announcements: Real Time Price Discovery in Foreign Exchange, *American Economic Review* 93(1): 38-62.

Antoniou, A., N. Ergul and P. Holmes, 1997, Market efficiency, thin trading and non-linear behaviour: evidence from an emerging market, *European Financial Management* 3(2): 175–190.

Albuquerque, R. and C. Vega, 2008, Economic News and International Stock Market Co-movement, *Review of Finance* 13(3): 401-465.

Aliyu, S. U. R., 2009, Stock prices and Exchange rate Interactions in Nigeria: An Intra-Global Financial Crisis Maiden Investigation, *Munich Personal RePEc Archive* Paper Number 13283.

Al-Khazali, O.M., D.K. Ding and C.S. Pyun, 2007, A New Variance Ratio Test of Random Walk in Emerging Markets: A Revisit, *Financial Review* 42: 303-317.

Appiah-Kusi, J. and K. Menyah, 2003, Return predictability in African stock markets, *Review of Financial Economics* 12(3): 247.

Aydemir, O and E. Demirhan, 2009, The Relationship between Stock Prices and Exchange Rates Evidence from Turkey, *International Research Journal of Finance and Economics* ISSN 1450-2887 Issue 23.

Bauwens, L., W. B. Omrane and P. Giot, 2005, News Announcements, Market Activity and Volatility in the Euro/Dollar Foreign Exchange Market, *Journal of International Money and Finance* 24(7): 1031-1176.

Bhar, R. and B. Nikolova, 2009, Return, Volatility Spillovers and Dynamic Correlation in the BRIC Equity Markets: An Analysis using a Bivariate EGARCH Framework, *Global Finance Journal* 19(3): 203-218.

Bollerslev, T., 1986, Generalised Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics* 31: 307-327.

Bollerslev, T. and J. M. Wooldridge, 1992, Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Variances, *Econometric Reviews* 11: 143-172.

Bollerslev, T., R. Chou, and K, Kroner, 1992, ARCH Modelling in Finance: A Review of the Theory and Empirical Evidence, *Journal of Econometrics* 52: 4–59.

Boyd J. H., J. Hu, and R Jagannathan, 2005, The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks*, Journal of Finance* 9 (2): 647-672.

Brock, W., W. Dechert and J. Scheinkman, 1987, A Test for Independence Based On the Correlation Dimension, *Working Paper*, University of Wisconsin at Madison, University of Houston, and University of Chicago.

Cai, J., Y.L. Cheung, R.S.K. Lee, M. Melvin, 2001, Once in a generation yen volatility in 1998: fundamentals, intervention and order flow, *Journal of International Money and Finance* 20: 327-347.

Clare, A., and R. Courtenay, 2001, Assessing the Impact of Macroeconomic News Announcements on Security Prices under Different Monetary Policy Regimes, *Working Paper*, No. 125, Bank of England.

Cohen, K. J., G. A. Hawawini, R. A. Schwartz, and D. K. Whitcomb, 1983, Frictions in the Trading Process and the Estimation of Systematic Risk, *Journal of Financial Economics*12: 263-278.

Dickey, D.A. and W.A. Fuller, 1979, Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association* 74: 427–431.

Dimson, E., 1979 Risk Measurement When Shares are Subject to Infrequent Trading, *Journal of Financial Economics* 7: 197-226.

Doong, S-C., S. Y-Yang, and A. T. Wang, 2005, The Dynamic Relationship and Pricing of Stocks and Exchange Rates: Empirical Evidence from Asian Emerging Markets, *Journal of American Academy of Business, Cambridge* 7(1): 118-123.

Engle, R. F., 1982, Autoregressive Conditional Heteroskedasticity with Estimates of Variance of United Kingdom Inflation, *Econometrica* 50, 987-1008.

Engle, R. and B., Kelly, 2009, Dynamic Equicorrelation, *NYU Working Paper* No. FIN-08-038.

Engle, R.F. and V. K. Ng, 1993, Measuring and Testing the Impact of News and Volatility, *Journal of Finance* 48: 1749-1778.

Evans, M. and R. Lyons, 1999, Order flow and exchange rate dynamics, *Berkeley Working paper.*

Fowler, D. J. and C. H. Rorke, 1983, Risk Measurement when Shares are Subject to Infrequent Trading- Comments, *Journal of Financial Economics* 12: 279-283.

Granger, C.W.J., B. Huang and C. Yang, 2000, A Bivariate Causality between Stock Prices and Exchange Rates: Evidence from Recent Asian Flu, *The Quarterly Review of Economics and Finance* 40: 337-354.

Gwilym, O. and M. Buckle, 2001, The Lead-Lag Relationship between the FTSE 100 Stock Index and its Derivative Contracts, *Applied Financial Economics* 11(4): 385-393.

Karolyi, G. A., R. M. Stulz, 1996, Why Do Markets Move Together? An Investigation of US-Japan Stock Return Co-movements, *The Journal of Finance* 51: 951-985.

Kauffman, K. and A. Weerapana, 2006, The Impact of AIDS-Related News on Exchange Rates in South Africa*, Economic Development and Cultural Change* 54(2): 349-68**.**

Koutmos, G., 1996, Modelling the dynamic interdependence of major European stock markets. *Journal of Business Finance and Accounting* 23: 975-988.

Lo, A and A. C. MacKinlay, 1990, An econometric analysis of infrequent trading, *Journal of Econometrics* 45: 181-211.

McInish, T.H., and R.A. Wood, 1986, Adjusting for Beta Bias: An Assessment of Alternate Techniques: A Note, *Journal of Finance* 41: 277-286.

Melvin, M., Yin, X., 2000, Public Information Arrival, Exchange Rate Volatility and Quote Frequency, *The Economic Journal* 110: 644-661.

Miller, M. H., J. Muthuswamy and R.Whaley, 1994, Mean Reversion of Standard and Poor 500 Index Basis Changes: Arbitrage-Induced or Statistical Illusion, *Journal of Finance* 49: 479-513.

Mishra, K. A., 2004, Stock Market and Foreign Exchange market in India: Are they related? *South Asia Economic Journal* 5(2): 209-232.

Mlambo, C. and N. Biekpe, 2005, Thin Trading on African Stock Markets: Implications for Market Efficiency Testing, *Investment Analyst Journal* 61: 29-40.

Mlambo, C. and N. Biekpe, 2007, Thin Trading on African Stock Markets: Implications for Market Efficiency Testing, *Investment Analyst Journal* 66: 5-18.

Nelson, D. B., 1991, Conditional Heteroskedasticity in Asset Returns; A New Approach, *Econometrica* 59(2): 347–370.

Osei, K. A., 2006, Macroeconomic Factors and the Ghana Stock Market, *The African Finance Journal*, 8(1): 26-38.

Phylaktis, K., and F. Ravazzolo, 2005, Stock Prices and Exchange Rate Dynamics, *Journal of International Money and Finance* 24: 1031-1053.

Rahman M. L.and J. Uddin, 2009, Dynamic Relationship between Stock Prices and Exchange Rates: Evidence from Three South Asian Countries, *International Business Research* 2 (2): 168-174.

Rayhorn, C., M.K. Hassan, J.S. Yu and K.R. Janson, 2007, Emerging Market Efficiencies: New Zealand's Maturation Experience in the Presence of Non-linearity, Thin Trading and Asymmetric Information, *International Review of Finance* 7: 21-34.

Scholes, M. and J. Williams, 1977, Estimating Betas from Nonsynchronous Data, *Journal of Financial Economics* 5: 309-328.

Stoll, H. R. And R. Whaley, 1990, The Dynamics of Stock Index Futures Returns, *Journal of Financial and Quantitative Analysis* 25: 441-468.

Smyth, R. and M. Nandha, 2003, Bivariate Causality between Exchange Rates and Stock Prices in South Asia, *Applied Economics Letters* 10: 699–704.

Tabak, B. M., 2006, Dynamic Relationship between Stock Prices and Exchange Rates: Evidence for Brazil, *Bank of Brazil Working Paper Series* 124.

Appendix A

Time Series Graphs for Ghana Covering the Period 1st August 2005 to 30th April 2010

Figure 1a. S&P BMI Total Return Index

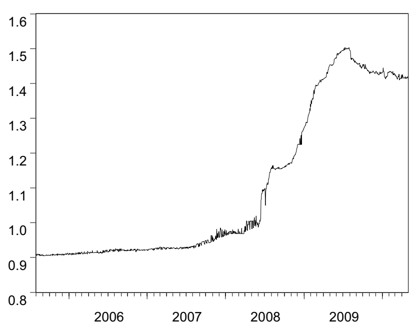

Figure 1b. Cedi/Dollar Price Index

Logarithmic Retuns

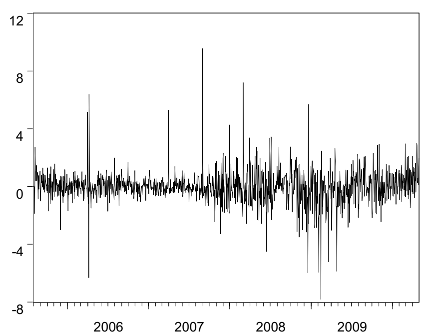

Figure 1c. Adjusted Stock Market Returns

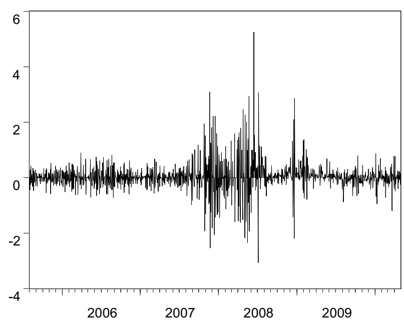

Figure 1d. Cedi/Dollar Returns

Time Series Graphs for Nigeria Covering the Period 1st August 2000 to 30th April 2010

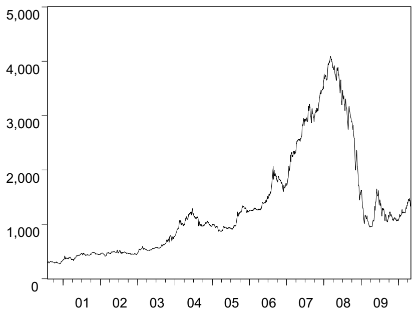

Figure 2a. S&P BMI Total Return Index

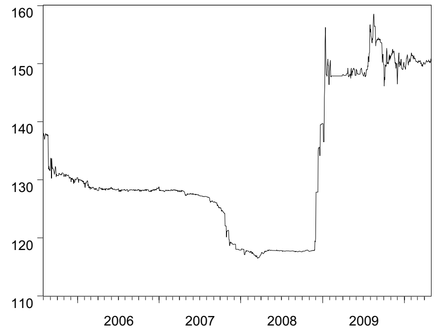

Figure 2b. Naira/Dollar Price Index

Logarithmic Retuns

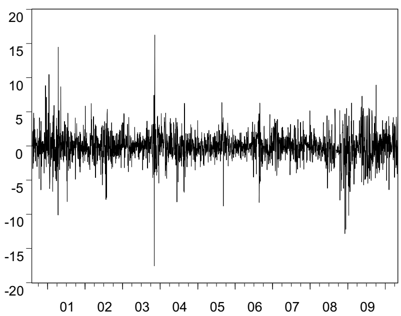

Figure 2c. Adjusted Stock market Returns

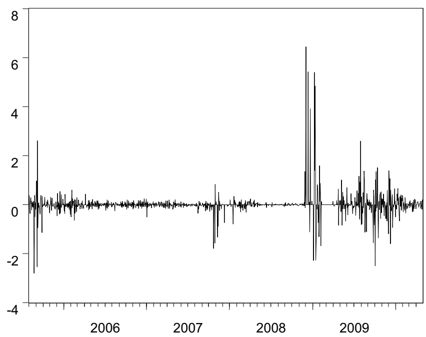

Figure 2d. Naira/Dollar Returns

Table 1. Data Characteristics on the Stock Exchanges from the Years 2006-2009

Year	Country	Date market opened	Number of listed companies	Market capitalization in US$ billion	Trading volume million	Turnover ratio (%)	Market capitalization as % of GDP
Year 2009							
	Ghana	1990	35	11.15	0.10	2.10	73.70
	Nigeria	1960	266	47.75	102.85	23.38	39.79
Year 2008							
	Ghana	1990	35	14.91	0.55	2.10	109.00
	Nigeria	1960	213	80.60	193.14	21.86	41.90
Year 2007							
	Ghana	1990	32	12.74	0.29	1.14	96.00
	Nigeria	1960	212	105.65	138.00	28.21	84.00
Year 2006							
	Ghana	1990	32	0.12	0.10	0.42	97.00
	Nigeria	1960	202	40.32	36.70	14.70	28.28

Source: The African Security Exchanges Association year books located at http://www.africansea.org/asea/library.aspx

Time Varying Conditional Discrete Jumps in Emerging African Equity Markets

Saint Kuttu

Hanken School of Economics, Department of Finance and Statistics, P.O. Box 287, FIN-65101 Vaasa, Finland. Phone: +358(0)403521758, Fax: +358(6)3533703, Email: saint.kuttu@hanken.fi

June 8, 2012

Abstract

An ARJI-GARCH model of Chan and Maheu (2002) is used to examine the time varying conditional jumps dynamics for thinly traded adjusted equity returns of Egypt, Nigeria and South Africa. The findings suggest that conditional jumps are time varying, and jumps are sensitive to past shocks for Egypt and South Africa but not for Nigeria. Jump sensitivity is persistent in all the markets, and only South Africa is more likely to exhibit asymmetric jump volatility. We provide evidence that the presence of thin trading leads to spurious estimates, and in some cases it understates the economic significance of the jump dynamics.

Keywords: conditional jumps, poisson process, ARJI-GARCH, thin trading, emerging equity markets.

JEL classification: C22, G15

---

*I am grateful to Professors Johan Knif (my research supervisor), Kenneth Högholm, Seppo Pynnönen and Peihwang Wei, participants at the 51st Annual Conference of the Southwestern Finance Association, Sheraton New Orleans, and Hanken 2011 Finance Seminar Participants in Vasa, Finland, for useful comment. All errors and omissions are solely mine.
Contact: Department of Finance and Statistics, Hanken School of Economics, P.O. Box 287, Vasa, Finland.

1 INTRODUCTION

Volatility in equity markets can amplify losses and magnify gains. Without volatility, hedging strategies and investment in derivative instruments may not be profitable. When volatility is conditional and continuous, some investors may be able to predict the trajectory of the volatility. Conversely, discrete jumps are difficult to predict. The purpose of this study is to contribute to the literature by examining the time-varying discrete jump dynamics in the equity markets of Egypt, Nigeria and South Africa. By market capitalization, the South African equity market is the largest in Africa, followed by Egypt and Nigeria. The 2008 financial crisis brought to the fore the relative resilience of emerging equity markets and their ability to lead the world out of the financial quagmire. Moreover as investors are increasingly turning attention to African equity markets for diversification, this study will help investors understand the evolution of the volatility process on these equity markets.

A number of studies have examined jump dynamics in a variant of jump models. For example, Evans (2011) employed non-parametric intraday jump detection procedures; Lee and Hannig (2010) used the Levy Jump Diffusion Process; Lin and Lee (2010) used the correlated bivariate Poisson Jump Intensity model; Lee and Mykland (2008) used Poisson-type jump test; Huang and Tauchen (2005) employed Power and Bipower Variation with Stochastic Volatility methodology; Maheu and McCurdy (2004) employed a mixed Generalised Autoregressive Conditional Heteroskedasticity (GARCH) Jump model; Pan (2002) used the Implied State Generalised Method of Moments approach; and Chan and Maheu (2002) used the Autoregressive Jump Intensity GARCH (ARJI-GARCH here after) model and document evidence of jump diffusion in the U.S. equity market. Likewise, Dungey and Hvozdyk (2012) used a formal joint test of cojumping, and Jiang, Lo, and Verdelhan (2011) employed Variance Swap Bipower Variation tests and document jump behaviour in the US treasury market. Chan (2008) used a bivariate GARCH-Jump model augmented with autoregressive jump intensity and found significant jump components in the treasury and in the currency spot market for the British pound, Canadian dollar, euro, Japanese yen and the Swiss franc. Similarly, on the commodity market, Chiou and Lee (2009) and Gronwald (2009) used the ARJI- GARCH model and found evidence of conditional jump behaviour in the oil market.

The purpose of this paper is to examine whether conditional discrete jumps on emerging African equity markets are time-varying. To our knowledge, the issue of time-varying conditional discrete jumps has not been examined on these markets or on markets with pervasive thin trading. To this end, this study attempts to add to the literature by investigating the conditional jump dynamics in the equity markets of Egypt, Nigeria and South Africa. This study assumes that equity-market innovations follow a Poisson process. Hence, the mean reverting Autoregressive Jump Intensity - GARCH (ARJI-GARCH) model of Chan and Maheu (2002) is used for this study. Thin trading, which introduces series of bias in empirical results (Lo and Mackinlay, 1990), is adjusted by applying the Miller, Muthuswamy and Whaley (1994) methodology to the data series.

The results suggest that for the equity markets of Egypt and South Africa, conditional jumps are time varying and jumps are sensitive to past shocks. However, for Nigeria we find that the jump intensity is constant, and jumps become sensitive when the conditional mean and the conditional variance of the distribution are a function of past returns. Jump sensitivity is, however, persistent in all the equity markets. Only the equity market of South Africa displays jump volatility asymmetry. This phenomenon may be attributed to the relative wide breadth and depth of the South African equity market. When the ARJI-GARCH model was applied to the logarithmic (non-adjusted return series) returns, we find that thin trading may understate the economic significance of the jump for Nigeria in the case of the constant model. For the rest of the models, we obtained spurious estimates, which may be due to the impact of thin trading. Clearly, the results indicate that adjusting for thin trading improves model estimation which may assure consistent estimates.

The rest of this paper is organised as follows. Section Two captures the economic and equity market features of the countries under consideration, Section Three presents the model of analysis, Section Four reviews the data, Section Five presents and discusses the empirical findings, and, lastly, Section Six captures the conclusion.

2 ECONOMIC AND EQUITY MARKET CHARACTERISTICS OF THE COUNTRIES STUDIED

The equity markets of Egypt, Nigeria and South Africa have enjoyed mixed performance in recent times; for instance, in Table 1, it can be observed that in 2007 only the equity market in South Africa posted returns less than 20%. However, in 2008 when the global financial meltdown spasm was felt across the world, all the three markets under study posted negative returns. In 2010, all the equity markets posted positive returns. Furthermore, in 2009, the equity market in Nigeria was still reeling under the global financial meltdown and posted negative returns. Clearly, it is safe to say that the impact of the 2008-2009 global financial crisis on the emerging equity markets of Africa is varied and uneven. In 2010, all the markets posted positive year-on-year returns.

Table 1. Equity Market Performance from 2005 to 2010 in Percentage

Year	Egypt	Nigeria	South Africa
2010	15.71	18.93	16.09
2009	35.00	-33.80	28.63
2008	-56.43	-45.77	-26.28
2007	51.29	74.73	16.64
2006	N/A	37.68	37.60
2005	146.29	N/A	42.98

Source: The African Security Exchanges Association located at http://www.africansea.org/asea/library.aspx

The real gross domestic products (GDP) reported in Table 2 for Egypt, Nigeria and South Africa were 5.1%, 8.4 % and 2.8% respectively in 2010, and in 2011, the real GDPs were 1.8%, 7.2% and 2.7% respectively. For 2012, they are forecasted to be 1.5%, 7.1% and 2.7% respectively. The lower figure of 1.5% for Egypt was due to the negative effect of the social and political unrest that occurred in the early part of 2011 on the economy.

Table 2. Real Gross Domestic Product (%)

Year	Egypt	Nigeria	South Africa
2012	1.5	7.1	2.7
2011	1.8	7.2	3.1
2010	5.1	8.4	2.8
2009	4.7	7.0	-1.7
2008	7.2	6.0	3.6
2007	7.1	7.0	5.6
2006	6.8	6.2	2.9

The GDP figures were culled from IMF World Economic Outlook Publication, April 2011 located at http://www.imf.org/external/pubs/ft/weo/2012/01/pdf/text.pdf
*Projected figures

With the swathe of austerity measures, which have been imposed by various European governments aimed at reining in the downward spiral of the euro and stabilising the European and world equity markets, economists predict that the austerity measure will stifle the fragile recovery from the 2008 financial crisis. Projections by the International Monetary Fund, for instance, show that accumulated real GDP growth for European economies will be -1.6% and 0.4% for 2012 and 2013 respectively, compared with 5.4% and 5.3% for the same period for the Sub-Saharan African economies[15].

[15] See IMF World Economic Outlook Publication, April 2012, http://www.imf.org/external/pubs/ft/weo/2012/01/pdf/text.pdf

Table 3. Institutional and Trading Arrangement on Sample Country Equity Markets as at the End of 2010

Market	Trading hours	Trading Method	Settlement cycle	Index	Tax Rates (dividends, interest, capital gain)	Restrictions on Foreign Participation
Egypt	10:30-14:30 Sun-Thu	Intra-day Trading, Online Trading.	T+2	CASE 30 Index	No Taxes	No
Nigeria	09:30 -14:30. Mon-Fri	Intra-day Trading, Online Trading.	T + 3	NSE All Share	10% on dividend, no capital gains tax.	No
South Africa	09:00 -17:00. Mon-Fri	Margin Trading, Intra-day Trading, Online Trading, Short Selling and Borrowing.	T + 5	JSE All Share	No taxes imposed on dividends for Non Residents, Interest 12%; Royalties, Visiting Entertainers 5%.	No

Source: The African Security Exchanges Association located at http://www.africansea.org/asea/library.aspx

Table 4. Data Characteristics on the Stock Exchanges from the Years 2006 to 2010

Year	Country	Date market opened	Number of listed companies	Market capitalization in US$ billion	Trading volume million	Turnover ratio (%)	Market capitalization as % of GDP
Year 2010							
	Egypt	1898	373	84.10	33.43	42.9	40.46
	Nigeria	1960	217	66.20	93.34	8.00	31.00
	South Africa	1887	407	1,012.1	71.25	44.64	12.45
Year 2009							
	Egypt	1898	306	91.08	36.60	49.90	73.70
	Nigeria	1960	266	47.75	102.85	23.38	39.79
	South Africa	1887	410	91.08	36.60	49.90	48.10
Year 2008							
	Egypt	1898	373	85.84	24.49	70.30	53.00
	Nigeria	1960	213	41.90	193.14	21.86	41.90
	South Africa	1887	425	549.20	85.78	71.84	19.59
Year 2007							
	Egypt	1898	435	136.69	15.061	38.73	105.07
	Nigeria	1960	212	105.65	138.00	28.21	84.00
	South Africa	1887	422	802.37	71.10	142.70	28.28
Year 2006							
	Egypt	1898	595	93.35	9.08	48.70	80.00
	Nigeria	1960	202	40.32	36.70	14.70	28.28
	South Africa	1887	401	889.94	13.15	42.08	34.49

Source: The African Security Exchanges Association year books located at http://www.africansea.org/asea/library.aspx

In Table 3, we can see that all the equity markets have no restriction on foreign participation, but Nigeria and South Africa have various taxes. Egypt and Nigeria open for 4 and 5 hours respectively, which are relatively short periods compared to South Africa which opens for 8 hours, 5 days per week. The descriptive data on the equity markets of Egypt, Nigeria and South Africa are presented in Table 4. It can be inferred from Table 4 that the turnover ratio for all countries is less than 50%, showing that the three equity markets are grappling with low liquidity as a consequence of the prevalence of thin trading. To draw any meaningful conclusion from empirical work on these three markets, thin trading should be taken into account.

3 METHODOLOGY

3.1 Thin Trading Adjustment

Daily returns for each series are computed by taking the first difference of the natural logarithm of the total return index multiplied by 100. Thus,

$$r_t = \ln\,(I_t/I_{t-1}) * 100, \tag{1}$$

where I_t and I_{t-1} represent the current days close and the previous day close respectively. Using the logarithmic procedure will make the series more likely to be stationary over time. The assumption underlying the logarithmic procedure is that stock returns are log-normal and continuously traded. In the presence of thin trading, this assumption will not hold.

Appiah-Kusi and Menya (2003) and Mlambo and Biekpe (2005) have documented pervasive thin trading on Egyptian, Nigerian and South African equity markets. Scholes and Williams (1977), Dimson (1979) Fowler and Rorke (1983), and Lo and MacKinlay (1990) have come to a consensus that thin trading introduces a potential bias in empirical work and conclusions drawn from such work might be misleading. Thin or infrequent trading occurs when stocks do not trade at every consecutive interval, and this can potentially lead to spurious autocorrelation in the return series.

Cohen, Hawawini, Schwartz, and Whitcomb (1983) and Miller, Muthuswamy and Whaley (1994) are among the number of studies that have proposed methods for correcting for thin trading. However, the Miller et al. (1994) model, followed by Appiah-Kusi and Menya (2003), Al-Khazali, Ding and Pyun (2007) and Rayhorn, Hassan, Yu and Janson (2007), is adopted for this study. This is because McInish and Wood (1986) argue that the Cohen et al. (1983) method provides an insignificant reduction in the magnitude of bias in beta estimates. The Miller et al. (1994) model uses a moving average that reflects the number of non-trading days to eliminate the effect of thin trading and calculates returns adjusted for the effect of non-trading days. Miller et al. (1994)[16] have shown that an AR(1) model can be estimated from which the non-trading adjustment can be obtained as follows:

$$r_t = \alpha + \beta r_{t-1} + \varepsilon_t. \tag{2}$$

Using the residuals (ε_t) from Equation (2), the adjusted returns are estimated as follows:

$$r_t^{adj} = \varepsilon_t/(1-\beta), \tag{3}$$

where r_t^{adj} is the return at time t adjusted for thin trading and assumes that the non-trading adjustment required to correct return is constant over time. Antoniou, Ergul and Holmes (1997), however, argue that this assumption may hold for highly liquid stock and for the three emerging African equity markets where illiquidity and thin trading are documented, adjustment is more likely to be time dependent. Hence, we employ the recursive least squares estimation technique in estimating Equation (2).

[16] See Miller et al. (1994) for proof

3.2 Autoregressive Jump Intensity- GARCH Model

This paper applies the Chan and Maheu (2002) method[17] which combines conditional jumps with the frequently applied GRACH models. The information set at time t is defined to be the history of returns, $\Phi_t = [r_t^{adj} .,.,.,r_1^{adj}]$. Consider the following jump model:

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i \, r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k.} \tag{4}$$

To simplify the construction of the likelihood, $z_t \backsim NID(0,1)$ and the conditional jump size, $X_{t,k} \backsim N(\theta_t, \delta_t^2)$. However, the model does not depend on these assumptions. The h_t follows a GARCH (p,q) (Bollerslev, 1986) process:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i}, \tag{5}$$

where $\epsilon_t = r_t^{adj} - \mu - \sum_{i=1}^{T} \phi_i \, r_{t-i}^{adj}$. The n_t , which describes the discrete number of jumps that arrive between $t-1$, and t, follows a Poisson distribution with $\lambda_t > 0$ and density

$$p(n_t = j|\Phi_{t-1}) = \frac{\lambda_t^j}{j!} e^{-\lambda_t}, \qquad j = 0,1,2,\ldots \tag{6}$$

where λ_t called the jump intensity is the mean and variance of the Poisson random variable. λ_t is permitted to vary with time, and knowledge of the information at $t-1$ implies knowledge of λ_t. A constant jump-intensity model with $\lambda_t = \lambda$, $\theta_t = \theta$ and $\delta_t^2 = \delta^2$, and three variants of time-varying jump intensity models are applied. For the latter, the jump-intensity, λ_t, is assumed to follow the autoregressive process

$$\lambda_t = \lambda_0 + \sum_{i=1}^{u} \rho_i \, \lambda_{t-i} + \sum_{i=1}^{v} \gamma_i \, \xi_{t-i} \, . \tag{7}$$

The jump intensity residual ξ_t is calculated as

[17] See Chan and Maheu (2002) for an elaborate exposition.

$$\xi_{t-i} \equiv E[n_{t-1}|\Phi_{t-1}] - \lambda_{t-i} = \sum_{j=0}^{\infty} jP(n_{t-i}|\Phi_{t-i}) - \lambda_{t-i}. \tag{8}$$

$E[n_{t-1}|\Phi_{t-1}] - \lambda_{t-i}$ is the expectation of the number of jumps using information at time $t-i-1$, and $\sum_{j=0}^{\infty} jP(n_{t-i}|\Phi_{t-i}) - \lambda_{t-i}$ is the inference on the average number of jumps at time $t-i$ based on time $t-i$ information. The term ξ_{t-i} denotes the unpredictable component affecting the inference about the conditional mean of the counting process η_{t-i}. Using observation r_t and the Bayes rule, the probability of the occurrence of j jumps at time t can be defined as

$$P(n_t = j|\Phi_t) = \frac{f(r_t|n_t = j, \Phi_{t-1})P(n_t = j|\Phi_{t-1})}{P(r_t|\Phi_{t-1})}$$
$$\text{for } j = 0,1,2,\ldots, \tag{9}$$

where $P(n_t = j|\Phi_t)$ is from equation (6). The distribution of the jump size, which follows a Gaussian distribution may change and display conditional dynamics. The following permits the conditional mean and conditional variance of the jump size distribution to be conditionally normal and a function of past returns:

$$\theta_t = \eta_0 + \eta_1 r_{t-1} D(r_{t-1}) + \eta_2 r_{t-1}\big(1 - D(r_{t-1})\big) \tag{10}$$

and

$$\delta_t^2 = \zeta_0^2 + \zeta_1 r_{t-1}^2, \tag{11}$$

where $D(x) = 1$ if $x > 0$ and 0 otherwise, and $\eta_0, \eta_1, \eta_2, \zeta_0$ and ζ_1 are parameters to be estimated. This specification of the conditional mean of the jump size provides some flexibility with regards to where jumps are centred. For instance, if the market experiences a gain (decline) in the last period, then today's conditional mean of the jump size is $\eta_0 + \eta_1 r_{t-1}, (\eta_0 + \eta_2 r_{t-1})$. This implies that the first moment of the jump size distribution can react to whether the last period's market return was positive or negative and to the magnitude of the return. This construction may capture the upturn after an equity market crash through a change in jump direction. For this effect to be captured, we would expect $\eta_2 < 0$. We allow r_{t-1}^2 to affect δ_t^2 to enable us to investigate whether the jump size variance is sensitive to the overall level of market volatility. We label equation (7) as ARJI-r_{t-1}^2. We are also interested in whether the variance of the jump size is a function of the GARCH volatility. Thus,

$$\delta_t^2 = \zeta_0^2 + \zeta_1 h_t, \tag{12}$$

which denotes ARJI-h_t. The difference between Equations (11) and (12) is that whereas the lagged squared return is a proxy for the last period's markets volatility, h_t is a prediction of the time t GARCH volatility component of the model. Intuitively, if the variance of the jump size is sensitive to contemporaneous market volatility, Equation (12) may capture this effect better that Equation (11). The Broyden, Fletcher, Goldfarb and Shanno (BFGS) algorithm (in RATS ™ 7.3) is used to maximise the log likelihood function via Quasi-Maximum Likelihood Estimation (QMLE) which is robust to the distribution of the disturbance term. The QMLE also assures consistent estimates of the parameters (Bollerslev and Wooldridge, 1992).

4 DATA

The data set consists of daily closing total equity market indices for Egypt, Nigeria and South Africa. The equity market indices are the S&P Egypt BMI total index, the S&P Nigeria BMI total index and the S&P South Africa IFCI total index. The sample runs from 1st January, 2001, to 31st December, 2010, yielding 2,610 observations. The data set is obtained from DataStream, which is denominated in US dollars, it adjusted for dividends.

Table 5. Summary Statistics of Adjusted Returns. 2001 to 2010

Statistic	Egypt	Nigeria	South Africa
Mean	0.0505	-0.053	0.007
Median	0.077	-0.072	0.043
Std. Dev.	1.780	2.063	1.743
Skewness	-0.506	-0.307	-0.358
Kurtosis	25.126	7.503	7.286
Jarque-Bera	53352.30**	2245.69**	2054.44**
LB(12)for r	52.250**	29.837**	24.800**
LB(12) for r_t^2	541.170**	468.230**	1777.00**
ARCH (p)	0.262**	0.205**	0.262**
ADF	-45.009**	-32.235**	-50.247**

**denotes statistically significant at 5%, Arch (p) is the Engle (1982) test for ARCH up to lag order 1, LB(12) is Ljung–Box Q-statistic at lag 12 and ADF denotes Augmented Dickey Fuller unit root test.

As can be seen in Table 5, normality is rejected in all markets. This is consistent with the application of a nonlinear model. However, there is dependence in the return and squared return series. There is also a significant ARCH effect in all the series, and this makes a compelling case for the application of a heteroskedastic model. Lastly, the null of unit root is rejected in all the series.

5 EMPIRICAL FINDINGS

Tables 6, 7 and 8 report a series of model estimates for the simplest constant intensity jump model over the different sub-sample periods. Thus 2001-2005 and 2006-2010. The restrictions $\lambda_t = \lambda$, $\theta_t = \theta$ and $\delta_t^2 = \delta^2$ are imposed in the ARJI model. The GARCH parameters are highly significant for countries in all the sub-sample periods. Thus, volatility is high and persistent in all the markets.. The mean of the jump size, θ, is negative and statistically significant for Egypt and South Africa during the 2006-2010 sub-sample, and the standard error of jump size, δ, is positive and highly significant for Egypt and Nigeria and, negative and significant for South Africa. Clearly, the results show that the standard error of the jump size is higher in the first sample than in the second sample.

Table 6. GARCH (1,1) Estimates for Egypt, Nigeria and South Africa. 2001 2010

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i \, r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2),$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i},$$

Parameter	Egypt	Nigeria	South Africa
ω	0.105**	0.120**	0.074**
α	0.071**	0.102**	0.107**
β	0.891**	0.869**	0.867**

**denotes statistically significant at 5%.

However, given a statistically significant mean of the jump size, θ, recorded for the second sample for Egypt and South Africa, the jump is relevant between 2006 and 2010. For Nigeria, however, the jump size does not matter. Also, in agreement with Chan and Maheu (2002), we find that the mean of the jump size, θ, for all three countries exhibits instability over time. The standard error of jump size, δ, is, however, fairly stable over time for all three countries.

Table 7. Estimates of the Constant Intensity Jump Model for Different Sample Periods for Egypt

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i \, r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2),$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i},$$
$$p(n_t = j|\Phi_{t-1}) = \frac{\lambda_t^j}{j!} e^{-\lambda_t}, \quad z_t \backsim NID(0,1)$$

Parameter	2001-2005	2006-2010
μ	0.137**	0.139**
	(3.680)	(3.165)
ϕ_1	0.225**	0.075**
	(4.040)	(2.842)
ϕ_2	-0.073**	-0.005
	(-2.326)	(-0.204)
ω	0.296**	0.025**
	(3.347)	(4.025)
α	0.114**	0.065**
	(4.788)	(3.759)
β	0.696**	0.904**
	(5.752)	(4.689)
δ	0.993**	0.950**
	(3.900)	(3.206)
θ	0.476	-0.723**
	(0.444)	(-3.149)
λ	0.025**	0.257**
	(2.465)	(3.093)
$Q^2(12)$	12.941	19.198
$Q_{\zeta_T}(12)$	113.332	45.508
Log-likelihood	-2421.96	-2379.90

**denotes statistically significant at 5%, numbers in parenthesis are t statistics. $Q^2(12)$ and $Q_{\zeta_T}(12)$ are the Ljung–Box Q-statistic at lag 12 for the squared standardized residuals and the jump intensity residuals respectively. . μ, ϕ_1, ϕ_2 are estimates from the mean equation estimation, ω, α, β are form the GARCH equation estimation, δ, θ, λ, are estimates from the constant Jumps model, and $Q^2(12)$, $Q_{\zeta_T}(12)$ are the model diagnostics parameters

Table 8. Estimates of the Constant Intensity Jump Model for Different Sample Periods for Nigeria

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i \, r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2)$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i},$$
$$p(n_t = j | \Phi_{t-1}) = \frac{\lambda_t^j}{j!} e^{-\lambda_t}, \quad z_t \backsim NID(0,1)$$

Parameter	2001-2005	2006-2010
μ	-0.04	0.012
	(-1.025)	(0.169)
ϕ_1	0.029	0.111**
	(0.991)	(3.996)
ϕ_2	0.080**	0.027
	(2.836)	(0.957)
ω	0.256**	0.007**
	(3.147)	(6.958)
α	0.113**	0.076**
	(4.297)	(5.432)
β	0.795**	0.898**
	(3.542)	(4.474)
δ	0.983**	0.952**
	(3.341)	(6.004)
θ	-0.720	-0.072
	(-0.519)	(-0.453)
λ	0.018	0.446**
	(1.396)	(2.623)
$Q^2(12)$	13.633	17.856
$Q_{\zeta_T}(12)$	39.99	26.251
Log-likelihood	-2635.54	-2685.23

**denotes statistically significant at 5%, numbers in parenthesis are t statistics. $Q^2(12)$ and $Q_{\zeta_T}(12)$ are the Ljung–Box Q-statistic at lag 12 for the squared standardized residuals and the jump intensity residuals respectively. . μ, ϕ_1, ϕ_2 are estimates from the mean equation estimation, ω, α, β are form the GARCH equation estimation, δ, θ, λ, are estimates from the constant Jumps model, and $Q^2(12)$, $Q_{\zeta_T}(12)$ are the model diagnostics parameters.

Table 9. Estimates of the Constant Intensity Jump Model for Different Sample Periods for South Africa

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i \, r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2),$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i},$$
$$p(n_t = j|\Phi_{t-1}) = \frac{\lambda_t^j}{j!} e^{-\lambda_t}, \quad z_t \backsim NID(0,1)$$

Parameter	2001-2005	2006-2010
μ	0.723**	0.600**
	(8.235)	(5.313)
ϕ_1	0.013	-0.008
	(0.442)	(-0.267)
ϕ_2	-0.001	-0.066
	(-0.036)	(-2.492)
ω	-0.030	0.005**
	(-4.036)	4.098
α	0.073**	0.087**
	(5.760)	(5.95)
β	0.861**	0.883**
	(9.953)	(6.179)
δ	-0.364**	-0.472**
	(-7.838)	(-2.837)
θ	-0.120**	-0.728**
	(-8.153)	(-7.325)
λ	0.999	0.827**
	(10.116)	(7.245)
$Q^2(12)$	9.363	19.136
$Q_{\zeta_T}(12)$	45.884	71.366
Log-likelihood	-2194.82	-2612.23

**denotes statistically significant at 5%, numbers in parenthesis are t statistics. $Q^2(12)$ and $Q_{\zeta_T}(12)$ are the Ljung–Box Q-statistic at lag 12 for the squared standardized residuals and the jump intensity residuals respectively. μ, ϕ_1, ϕ_2 are estimates from the mean equation estimation, ω, α, β are form the GARCH equation estimation, δ, θ, λ, are estimates from the constant Jumps model, and $Q^2(12)$, $Q_{\zeta_T}(12)$ are the model diagnostics parameters.

The result for the jump intensity parameter, λ, is shown to be time varying for Egypt for different sample periods, and in the full sample (reported in Table 10). Thus, for Egypt, the jump composite is higher in the second sub-sample than the first sub-sample. For Nigeria and South Africa, however, the jump intensity is time varying for the 2006-2010 sub-sample and the full sample (reported in Tables 11 and 12). The finding is in line with that reported by Chan and Maheu (2002) for the US equity market.

The finding is not surprising because the results mirror the major jumps that occurred as a consequence of the 2007-2008 global meltdown. The Ljung–Box Q-statistic for the jump intensity residuals supports variations in the jump intensity, λ, especially for Egypt.

Estimates of the simplest constant intensity jump model, the ARJI model with a constant jump size distribution and the fully dynamic jump models ARJI-r_{t-1}^2 and ARJI-h_t for Egypt, Nigeria and South Africa are reported in Tables 10, 11 and 12 respectively. The GARCH parameters are significant for Egypt and South Africa for all the models. For Nigeria, however, the GARCH effect is reduced when we allow the GARCH variance to interact with ARJI-r_{t-1}^2. Thus, the GARCH variance does not affect the jump intensity, λ, in the ARJI-r_{t-1}^2 model for Nigeria. The non-negativity and inevitability constraints are satisfied in all models. Also the GARCH parameters are stationary.

For Egypt and Nigeria, the standard error of the jump size, ζ_0, is highly significant for all but the ARJI-$h_t$variant of the models, and, for South Africa, it is significant for all variants. Also the mean of the jump size, η_0, is statistically significant for the ARJI-r_{t-1}^2 and ARJI-h_t models for Egypt, and for all variants of the model for South Africa. The jump parameter, λ, is significant for the ARJI, ARJI-r_{t-1}^2 and ARJI-h_t models for Egypt, and for South Africa it is significant for all models. Intuitively, the results show that conditional jumps are time varying and unconditional jumps are infrequent. This is also in line with the findings of Chan and Maheu (2002). For Nigeria, the time-varying conditional jump is rejected in favour of constant jumps.

The model does not however tell us the specific number of jumps; this would be left for future examination. The ρ, which measures persistence in jump sensitivity, γ, is highly significant for all three countries for the ARJI, ARJI-r_{t-1}^2 and ARJI-h_t models.

Economically, the persistence in jump sensitivity is mild for Egypt and strong for Nigeria and South Africa. Intuitively, this suggests a high probability of many jumps today being followed by a high probability of many jumps tomorrow (Chan and Maheu, 2002). Jumps are sensitive (γ) to past shocks for Egypt and South Africa in all the ARJI models. For Nigeria, the jump sensitivity is only captured in the ARJI-r_{t-1}^2 and ARJI-h_t models. Thus, a one percent increase in past shock results in a huge impact on the next period's jump intensity for Egypt and South Africa in all models. The diagnostics tests indicate that there is no autocorrelation in the squared standardises residuals, Q^2, and the jump intensity residuals, Q_{ζ_T}. Clearly, the ARJI models are able to capture the autocorrelation in the jump intensity residuals, ξ_t, that may be present in the constant model.

Table 10. Estimates of ARJI Models for Egypt, 2001-2010

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i \, r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2),$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i}, \quad \lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \, \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \, \xi_{t-i}$$
$\theta_t = \eta_0 + \eta_1 r_{t-1} D(r_{t-1}) + \eta_2 r_{t-1}\big(1 - D(r_{t-1})\big)$, ARJI- h_t:$\delta_t^2 = \zeta_0^2 + \zeta_1 h_t$, ARJI- r_{t-1}^2:$\delta_t^2 = \zeta_0^2 + \zeta_1 r_{t-1}^2$,

Parameter	Constant	ARJI	ARJI-r_{t-1}^2	ARJI-h_t
μ	0.093**	0.094**	0.011**	0.116**
	(3.467)	(3.200)	(3.260)	(3.645)
ϕ_1	0.155**	0.146**	0.144**	0.1358**
	(7.055)	(5.070)	(5.105)	(5.817)
ϕ_2	-0.042**	-0.049**	-0.044**	-0.047**
	(-2.134)	(-2.679)	(-2.206)	(-2.509)
ω	0.090**	0.021	0.019**	0.021**
	(3.558)	(1.958)	(2.554)	(2.308)
α	0.095**	0.019**	0.016**	0.016**
	(6.266)	(2.184)	(2.178)	(2.303)
β	0.826**	0.955**	0.959**	0.954**
	(5.677)	(4.904)	(5.962)	(4.360)
ζ_0	0.997**	0.716**	0.983**	0.580
	(2.836)	(4.322)	(4.470)	(0.226)
ζ_1			0.117	0.940
			(1.507)	(1.812)
η_0	-0.457	-0.266	-0.432**	-0.472**
	(-1.159)	(-1.521)	(-2.421)	(-2.028)
η_1			0.061	0.141
			(0.450)	(1.326)
η_2			-0.072	-0.081
			(-0.960)	(-0.905)
λ_0	0.074	0.062**	0.060**	0.093**
	(1.484)	(3.628)	(3.991)	(2.031)
ρ		0.589**	0.662**	0.536**
		(3.771)	(4.454)	(4.769)
γ		0.890**	0.662**	0.654**
		(4.699)	(2.903)	(4.269)
$Q^2(12)$	5.501	14.192	62.728	56.509
$Q_{\zeta_T}(12)$		23.443	17.379	15.656
Log-likelihood	-4706.42	-4695.88	-4691.61	-4687.91

**denotes statistically significant at 5%, numbers in parenthesis are *t* statistics. $Q^2(12)$ and $Q_{\zeta_T}(12)$ are the Ljung–Box Q-statistic at lag 12 for the squared standardized residuals and the jump intensity residuals respectively. μ, ϕ_1, ϕ_2 are estimates from the mean equation estimation, ω, α, β are form the GARCH equation estimation, ζ_0, ζ_1, η_0, η_1, η_2, λ_0, ρ, γ are estimates from the time varying Jumps model, and $Q^2(12)$, $Q_{\zeta_T}(12)$ are the model diagnostics parameters.

Table 11. Estimates of ARJI Models for Nigeria, 2001-2010

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i \, r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2),$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i}, \quad \lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \, \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \, \xi_{t-i}$$
$$\theta_t = \eta_0 + \eta_1 r_{t-1} D(r_{t-1}) + \eta_2 r_{t-1}\big(1 - D(r_{t-1})\big)$$, ARJI- h_t:$\delta_t^2 = \zeta_0^2 + \zeta_1 h_t$, ARJI- r_{t-1}^2:$\delta_t^2 = \zeta_0^2 + \zeta_1 r_{t-1}^2$,

Parameter	Constant	ARJI	ARJI-r_{t-1}^2	ARJI-h_t
μ	-0.283	-0.039	-0.050	-0.054
	(-0.823)	(-1.150)	(-1.431)	(-1.475)
ϕ_1	0.073**	0.075**	0.032	0.026
	(3.663)	(3.446)	(0.904)	(0.972)
ϕ_2	0.057**	0.057**	0.055**	0.054**
	(2.721)	(2.849)	(2.824)	(2.802)
ω	0.102**	0.878**	0.664	0.897**
	(2.967)	(2.704)	(1.626)	(5.704)
α	0.080**	0.092**	0.038	0.039**
	(4.067)	(2.845)	(0.926)	(2.638)
β	0.879**	0.403**	0.527	0.348**
	(4.682)	(2.096)	(1.945)	(4.142)
ζ_0	0.441**	0.968**	0.934**	0.001
	(3.609)	(3.925)	(3.225)	(0.080)
ζ_1			0.055	0.400**
			(1.658)	(4.907)
η_0	-0.485	-0.029	0.009	0.012
	(-0.949)	(-0.455)	(0.128)	(0.165)
η_1			0.038	0.039
			(1.212)	(1.345)
η_2			0.046	0.046
			(1.292)	(1.423)
λ_0	0.043**	0.014	0.021	0.023
	(2.896)	(1.189)	(1.153)	(1.895)
ρ		0.980**	0.979**	0.979**
		(4.681)	(4.642)	(4.352)
γ		0.548**	0.584**	0.570**
		(2.475)	(2.335)	(3.929)
$Q^2(12)$	13.381	13.896	24.319	27.426
$Q_{\zeta_T}(12)$		20.048	14.538	13.694
Log-likelihood	-5315.18	-5302.53	-5298.33	-5296.83

**denotes statistically significant at 5%, numbers in parenthesis are *t* statistics. $Q^2(12)$ and $Q_{\zeta_T}(12)$ are the Ljung–Box Q-statistic at lag 12 for the squared standardized residuals and the jump intensity residuals respectively. μ, ϕ_1, ϕ_2 are estimates from the mean equation estimation, ω, α, β are form the GARCH equation estimation, ζ_0, ζ_1, η_0, η_1, η_2, λ_0, ρ, γ are estimates from the time varying Jumps model, and $Q^2(12)$, $Q_{\zeta_T}(12)$ are the model diagnostics parameters.

Table 12. Estimates of ARJI Models for South Africa, 2001-2010

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2),$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}, \; \lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \xi_{t-i}$$
$$\theta_t = \eta_0 + \eta_1 r_{t-1} D(r_{t-1}) + \eta_2 r_{t-1}\big(1 - D(r_{t-1})\big), \text{ ARJI- } h_t{:}\delta_t^2 = \zeta_0^2 + \zeta_1 h_t, \text{ARJI- } r_{t-1}^2{:}\delta_t^2 = \zeta_0^2 + \zeta_1 r_{t-1}^2,$$

Parameter	Constant	ARJI	ARJI-r_{t-1}^2	ARJI-h_t
μ	0.670**	0.153**	0.177**	0.203**
	(4.373)	(4.347)	(5.761)	(5.234)
ϕ_1	0.006	-0.005	-0.003	-0.002
	(0.213)	(-0.287)	(-0.112)	(-0.865)
ϕ_2	-0.034**	-0.049**	-0.052**	-0.056**
	(-2.352)	(-2.596)	(-2.619)	(-2.961)
ω	-0.037**	0.005	0.005**	0.008**
	(-2.606)	(1.99)	(2.103)	(4.548)
α	0.080**	0.007**	0.008**	0.010**
	(4.277)	(2.191)	(3.866)	(4.332)
β	0.884**	0.985**	0.983**	0.977**
	(3.425)	(3.177)	(3.502)	(3.665)
ζ_0	0.461**	0.184**	0.905**	0.967**
	(3.149)	(4.033)	(5.049)	(4.666)
ζ_1			0.017	0.454**
			(1.256)	(5.666)
η_0	-0.199**	-0.178**	-0.330**	-0.369**
	(4.697)	(-2.325)	(-3.088)	(-4.747)
η_1			0.050	0.041**
			(0.908)	(2.56)
η_2			-0.057**	-0.065**
			(-2.194)	(-4.574)
λ_0	0.976**	0.035**	0.039**	0.054**
	(3.403)	(3.315)	(2.391)	(6.218)
ρ		0.957**	0.953**	0.930**
		(4.315)	(5.981)	(5.622)
γ		0.488**	0.939**	0.907**
		(3.343)	(4.020)	(4.819)
$Q^2(12)$	83.087	13.280	13.466	13.996
$Q_{\zeta_T}(12)$		56.002	62.733	55.364
Log-likelihood	-4784.64	-4776.24	-4770.02	-4768.03

**denotes statistically significant at 5%, numbers in parenthesis are *t* statistics. $Q^2(12)$ and $Q_{\zeta_T}(12)$ are the Ljung–Box Q-statistic at lag 12 for the squared standardized residuals and the jump intensity residuals respectively. μ, ϕ_1, ϕ_2 are estimates from the mean equation estimation, ω, α, β are form the GARCH equation estimation, ζ_0, ζ_1, η_0, η_1, η_2, λ_0, ρ, γ are estimates from the time varying Jumps model, and $Q^2(12)$, $Q_{\zeta_T}(12)$ are the model diagnostics parameters.

Estimates for the two models that extend the jump dynamics in the ARJI specification are reported in the last two columns of Tables 10, 11 and 12. Both the ARJI-r_{t-1}^2 and ARJI-h_t models allow the conditional mean and the conditional variance of the jump size distribution to be a function of past returns. The log-likelihood (LR) test shows that both models provide a significant improvement over the simper ARJI specification. Also, in line with Chan and Maheu (2002), the extensions do not seem to alter the dynamics found in the conditional intensity. For instance, jump intensity, λ, and volatility, ρ, are persistent for Egypt and South Africa, indicating that jump intensity is time varying. For Nigeria, however, the ARJI model and its extensions do not support the constant model. Since the LR test shows improvement in the ARJI models compared to the constant models, we argue that for Nigeria the jump intensity is generally not time varying despite persistence in the jump volatility.

Estimates from the ARJI-r_{t-1}^2 and ARJI-h_t models show that the jump direction in South Africa is asymmetric. The jump direction is, however, sensitive to the state of the stock market in all the three countries. The mean of the jump, η_0, is negative and statistically significant for Egypt and South Africa. This result is anticipated given that investors have a high probability of earning negative returns on both markets (negative skewness).

The asymmetric parameter, η_2, estimate for South Africa is significant and negative, which implies that after a stock market downturn, the direction of a jump in the next period is more likely to be positive than negative. This result also shows that a large negative return realisation due to jumps will cause an immediate increase in the variance. The reason for this phenomenon is that when jumps are realised, they tend to have a negative effect on returns. For Egypt and Nigeria, however, the direction of the jump size after a market decline cannot be determined. It can be said that, among the three equity markets, the jump asymmetry displayed by South Africa may be due to the relative breadth and the depth of the equity market.
The parameter of interest, the time-varying jump intensity, λ, implied by the model are depicted in figures 3, 6 and 9 for Egypt, Nigeria and South Africa respectively in Appendix A. For Egypt, the larger jump intensity around 2001, 2003 and to some extent 2005 mirrors the geopolitical Middle East crisis. For instance, the agreement between Egypt, Lebanon and Syria in December 2000 to build a billion-dollar pipeline to carry Egyptian gas to the Lebanese port of Tripoli, and the escalation of the

Palestinian-Israeli conflict in 2001, with calls by the Arab League to sever contacts with Israel[18], might have caused a significant jump in the Egyptian equity market in 2001. We also find that the 2003 Gulf war and 2006 Lebanon-Israeli conflict caused significant jump intensity in the equity market of Egypt around those times. Additionally, for Nigeria, the brutal spasm of religious and ethnic conflict that occurred in 2001 and 2005[19] seems to have impacted on the jump dynamics of the equity market. Also the conflicts leading up to the 2003 presidential and parliamentary elections cause jumps to increase in the Nigerian equity market. During the 2007 election, however, significant jumps were not observed. This may be because of structures put in place to assure a credible election. The significant jump intensity before and during 2008 for all three markets was the result of the 2008 global financial crisis.

Among the three equity markets under study, the equity market of Nigeria has the least market capitalisation and turnover ratio as of the end of 2009. This may suggest the breadth and depth of the markets is relatively limited, which may account for the jump intensity being time invariant.

Interestingly, we find that a 1% market decline in the last period results in about a 39% decline in today's conditional mean of the jump size[20] for the equity market of South Africa. Focusing on estimates from the ARJI-h_t models, which better capture the effect of jump sensitivity to contemporaneous market volatility, about 97% of the variance of the jump for the equity market of South Africa is sensitive to contemporaneous market volatility. Maheu and McCurdy (2004) argue that the average variance due to jumps is a better measure of the effect of jumps on returns. Hence, we estimate that the average conditional variance component associated with the jump innovation[21] to be about 6%. Clearly, for the South African equity market, which shows jump sensitivity to contemporaneous market volatility, only 6% percent of the jump sensitivity is priced. This shows that not all innovations are captured in prices of return which may be a reflection of the degree of information efficiency in the South African equity market. In the equity markets of Egypt and Nigeria, however, we find no effect of jump sensitivity

[18] Please see "Arabs seek to halt Israel contacts" http://edition.cnn.com/2001/WORLD/meast/05/19/mideast.03/

[19] See "Timeline of Nigerian "religious" conflict for year 2000 to 2010 leaving approximately 5,981 people dead" http://essdonli.wordpress.com/2011/01/09/timeline-of-nigerian-religious-conflicts-from-the-year-2000-to-2010-leaving-approximately-5981-people-dead/

[20] Calculated as $\eta_0 + \eta_2 r_{t-1}$

[21] Calculated as $(\eta_0^2 + \zeta_0^2)\lambda_i$

to contemporaneous market volatility, and no conditional variance component associated with the jump innovation.

On average, if the equity markets of Egypt and South Africa experience any form of jump innovation on a particular day, the jump intensity lasts for about 7 hours and 6 hours respectively[22]. For Nigeria where the jump intensity is not time varying, we find that averagely jump intensity lasts for about 34 days. Also on average, the life of volatility (volatility persistence) associated with jumps[23] lasts for about 1, 33 and 10 days for Egypt, Nigeria and South Africa respectively.

The reasons for the average life of volatility for the three countries' equity markets may not be far-fetched. For Egypt, the equity market is to a greater extent influenced by the geopolitical dynamics in the Middle East. Specifically the friction between Israel and its neighbours causes the equity market to react to any major development, but the reaction dies out after a day. For Nigeria, however, the reasons may be political and ethnic tensions with religious overtones which can last for days and that may explain the relatively long persistence in the average volatility associated with the jump. Lastly, for South Africa the reasons may hinge on the economic dynamics of the country rather than political.

A further robustness check was undertaken by applying the Chan and Maheu (2002) to returns not adjusted for thin trading. We find significant serial correlation in the squared standardised residuals, Q^2, and the jump intensity residuals, Q_{ζ_T}. In instances where there is no autocorrelation in the squared standardises residuals, Q^2, and the jump intensity residuals, Q_{ζ_T}, we find that the economic impact of the jump may be understated. Thus, the coefficients and the t- statistics were comparatively small for the non-adjusted returns (please see Tables 13, 14 and 15).

[22] We calculated the average life of jumps intensity as $ln(0.5)/ln(\lambda_i)$ and we get 0.29, 34 and 0.24 for Egypt, Nigeria and South Africa respectively

[23] Calculated as $ln(0.5)/ln(\rho_i)$

6 CONCLUSION

This paper examined the time varying conditional jumps in the equity markets of Egypt, Nigeria and South Africa. We adjusted for thin trading and applied an ARJI-GARCH model to a data of 2,610 observations.

The results suggest a significant time variation in the conditional jump intensity and jump size distribution in the equity markets of Egypt and South Africa. Intuitively, conditional jump intensity lasts for 7 hours and 6 hours for the equity markets of Egypt and south Africa respectively. When there is an incidence of jumps for Nigeria, the jumps are not time varying and when jumps occur, the intensity lasts for about 34 days. This may be a reflection of the social and economic fissures left by the convulsive ethnic and religious violence that can last for days. Jump sensitivity is persistent in all the equity markets.

We also find evidence that jumps are sensitive to past shocks in the equity markets of Egypt and South Africa in all the variants of the model. Jump sensitivity to past shocks only became apparent for Nigeria when we allowed the conditional mean and the conditional variance to be a function of past returns. We also find that only the equity market of South Africa displays jump volatility asymmetry and, economically, about 6% of the conditional variance component associated with jumps is priced in the return. This may be a reflection of the degree of information efficiency in the market.

The ARJI-GARCH model could not fully capture the heteroskedasticity when applied to the logarithmic (non-adjusted) returns. We find incidence of serial correlation in the squared standardised residuals and the jump intensity residuals. For Nigeria where the model worked under the constant model, we find that the presence of thin trading may be behind the reduction in the economic impact of the jumps. Clearly, from the foregoing, in agreement with Lo and Mackinlay (1990), we can deduce that the presence of thin trading in modelling may give bias estimates.

Overall, the findings shed some light on the extreme volatility on these markets which is very relevant for portfolio risk management, investments, and derivatives pricing.

Lastly, we suggest that the incidence of volatility jump asymmetry should be explored using an ARJI- exponential GARCH model. This is because the exponential GARCH model does not impose restrictions on the parameters and, by construction, it nests volatility asymmetry. Also, the incidence of jump intensity and number of jumps on the equity markets of Egypt, Nigeria and South Africa should be explored with high frequency data when available.

REFERENCES

Al-Khazali, O.M., D.K. Ding and C.S. Pyun, 2007, A New Variance Ratio Test of Random Walk in Emerging Markets: A Revisit, *Financial Review* 42: 303-317.

Appiah-Kusi, J. and K. Menyah, 2003, Return predictability in African stock markets, *Review of Financial Economics* 12(3): 247.

Chan, W. H., 2008, Dynamic Hedging with Foreign Currency Futures in the Presence of Jumps, *Studies in Nonlinear Dynamics and Econometrics*, 12, article 4.

Chan, W.K. and J.M. Maheu, 2002, Conditional Jump Dynamics in Stock Market Returns, *Journal of Business and Economic Statistics*, 20: 377-379.

Chiou, J.S. and Y.H. Lee, 2009, Jump Dynamics and Volatility: Oil and the Stock Markets, *Energy*, 34(6): 788-796.

Cohen, K. J., G. A. Hawawini, R. A. Schwartz, and D. K. Whitcomb, 1983, Frictions in the Trading Process and the Estimation of Systematic Risk, *Journal of Financial Economics*12: 263-278.

Gronwald, M., 2009, Jumps in Oil prices – Evidence and Implications, *CESifo Working Paper Series* No. 75.

Dimson, E., 1979, Risk Measurement When Shares are Subject to Infrequent Trading, *Journal of Financial Economics* 7: 197-226.

Dungey, M., M.,McKenzie, V. Smith, 2009a, News, No-news and Jumps in the US Treasury Market, *Journal of Empirical Finance* 16: 430-445.

Dungey, M. and L. Hvozdyk, 2012, *Cojumping*: *Evidence* from the *US Treasury Bond* and *Futures Markets*, *Journal of Banking and Finance* 36(5): 1563-1575.

Evans, K.P., 2011, Intraday jumps and US Macroeconomic News Announcements, *Journal of Banking and Finance* 35 (10): 2511-2527.

Fowler, D. J. and C. H. Rorke, 1983, Risk Measurement when Shares are Subject to Infrequent Trading, *Journal of Financial Economics* 12: 279-283.

Hunag, X. and G. T., Tauchen, 2005 The Relative Contribution of Jumps to Total Price Variance, *Journal of Financial Econometrics* 4: 456–499.

Jiang G. J., I. Lo, and A. Verdelhan, 2011, Information shocks, liquidity shocks, jumps, and price discovery: Evidence from the U.S. Treasury market, *Journal of Financial and Quantitative Analysis* 46:527-551.

Lee, S. S. and J., Hannig, 2010, Detecting Jumps from Lévy Jump Diffusion Processes, *Journal of Financial Economics* 96: 271–290.

Lee, S. and P.A., Mykland, 2008, Jumps in Fnancial Markets: A new Nonparametric Test and Jump Dynamics, *Review of Financial Studies* 21: 2535–2563.

Lin, C-T and Y-H. Lee, 2010, The Jump-diffusion Process for the VIX and the S&P 500 Index *African Journal of Business Management* 4(9): 1761-1768.

Lo, A and A. C. MacKinlay, 1990, An Econometric Analysis of Infrequent Trading, *Journal of Econometrics* 45: 181-211.

Maheu, J. M and T. McCurdy, 2004, News Arrival, Jump Dynamics, and Volatility Components for Individual Stock Returns, *The Journal of Finance* 59: 755-793.

McInish, T.H., and R.A. Wood, 1986, Adjusting for Beta Bias: An Assessment of Alternate Techniques: A Note, *Journal of Finance* 41: 277-286.

Miller, M. H., J. Muthuswamy and R.Whaley, 1994, Mean Reversion of Standard and Poor 500 Index Basis Changes: Arbitrage-Induced or Statistical Illusion, *Journal of Finance* 49: 479-513.

Mlambo, C. and N. Biekpe, 2005, Thin Trading on African Stock Markets: Implications for Market Efficiency Testing, *Investment Analyst Journal* 61: 29-40.

Pan J. 2002, The Jump-Risk Premia Implicit in Options: Evidence from an Integrated Time-Series Study, *Journal of Financial Economics* 63(1): 3-50.

Scholes, M. and J. Williams, 1977, Estimating Betas from Nonsynchronous Data, *Journal of Financial Economics* 5: 309-328.

Stoll, H. R. and R. Whaley, 1990, The Dynamics of Stock Index Futures Returns, *Journal of Financial and Quantitative Analysis* 25: 441-468.

Rayhorn, C., M.K. Hassan, J.S. Yu and K.R. Janson, 2007, Emerging Market Efficiencies: New Zealand's Maturation Experience in the Presence of Non-linearity, Thin Trading and Asymmetric Information, *International Review of Finance* 7: 21-34.

Table 13. Estimates of ARJI Models for Egypt (Non-Adjusted Return), 2001-2010

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i \, r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2),$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i}, \quad \lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \, \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \, \xi_{t-i}$$
$$\theta_t = \eta_0 + \eta_1 r_{t-1} D(r_{t-1}) + \eta_2 r_{t-1}\big(1 - D(r_{t-1})\big), \text{ ARJI- } h_t{:}\delta_t^2 = \zeta_0^2 + \zeta_1 h_t, \text{ ARJI- } r_{t-1}^2{:}\delta_t^2 = \zeta_0^2 + \zeta_1 r_{t-1}^2,$$

Parameter	Constant	ARJI	ARJI-r_{t-1}^2	ARJI-h_t
μ	0.0051	0.061**	0.070**	0.080**
	(1.702)	(2.041)	(2.025)	(2.518)
ϕ_1	0.093**	0.082**	0.082**	0.079**
	(4.416)	(4.040)	(2.623)	(2.483)
ϕ_2	-0.027	-0.032	-0.028	-0.031
	(-1.402)	(-1.697)	(-1.404)	(-1.639)
ω	0.081**	0.027**	0.024**	0.025**
	(2.532)	(2.249)	(2.410)	(2.662)
α	0.086**	0.024**	0.020**	0.019**
	(4.242)	(2.568)	(2.037)	(2.470)
β	0847**	0.944**	0.949**	0.948**
	(5.472)	(4.029)	(5.962)	(4.589)
ζ_0	0.965**	0.800**	0.924**	0.338
	(2.970)	(4.391)	(3.219)	(0.076)
ζ_1			0.189	0.746**
			(1.203)	(2.376)
η_0	-0.411	-0.292	-0.445	-0.430
	(-0.811)	(-1.366)	(-1.960)	(-1.902)
η_1			0.092	0.104
			(0.465)	(0.972)
η_2			-0.083	-0.071
			(-0.589)	(-0.625)
λ_0	0.043	0.060**	0.056**	0.093**
	(0.759)	(3.173)	(3.430)	(2.570)
ρ		0.535**	0.643**	0.478**
		(4.453)	(2.583)	(2.571)
γ		0.824**	0.570**	0.626**
		(4.998)	(2.076)	(3.008)
$Q^2(12)$	3.766**	13.361	16.769**	17.157**
$Q_{\zeta_T}(12)$		18.498**	12.203	14.941**
Log-likelihood	-4615.93	-4606.18	-4602.93	-4598.45

**denotes statistically significant at 5%, numbers in parenthesis are t statistics. $Q^2(12)$ and $Q_{\zeta_T}(12)$ are the Ljung–Box Q-statistic at lag 12 for the squared standardized residuals and the jump intensity residuals respectively. μ, ϕ_1, ϕ_2 are estimates from the mean equation estimation, ω, α, β are form the GARCH equation estimation, ζ_0, ζ_1, η_0, η_1, η_2, λ_0, ρ, γ are estimates from the time varying Jumps model, and $Q^2(12)$, $Q_{\zeta_T}(12)$ are the model diagnostics parameters.

Table 14. Estimates of ARJI Models for Nigeria (Non-Adjusted Return), 2001-2010

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2),$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}, \quad \lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \xi_{t-i}$$
$\theta_t = \eta_0 + \eta_1 r_{t-1} D(r_{t-1}) + \eta_2 r_{t-1}(1 - D(r_{t-1}))$, ARJI- h_t:$\delta_t^2 = \zeta_0^2 + \zeta_1 h_t$, ARJI- r_{t-1}^2:$\delta_t^2 = \zeta_0^2 + \zeta_1 r_{t-1}^2$,

Parameter	Constant	ARJI	ARJI-r_{t-1}^2	ARJI-h_t
μ	0.029	0.023	0.015	-0.061
	(1.297)	(0.738)	(0.496)	(-1.597)
ϕ_1	0.267**	0.259**	0.187**	0.162**
	(3.575)	(3.396)	(2.904)	(3.080)
ϕ_2	0.038	0.047**	0.037**	0.037
	(1.797)	(2.485)	(2.167)	(1.934)
ω	0.054**	0.005	0.002**	0.897**
	(2.764)	(1.559)	(2.426)	(5.703)
α	0.0783**	0.004	0.002**	0.008**
	(4.973)	(1.978)	(2.870)	(3.244)
β	0.879**	0.987**	0.993**	0.932**
	(4.622)	(2.748)	(2.539)	(3.789)
ζ_0	0.812**	0.922**	0.910**	-0.001
	(3.687)	(3.494)	(2.698)	(-0.001)
ζ_1			0.065**	0.753**
			(3.793)	(3.246)
η_0	-0.383	-0.005	0.010	0.034
	(-0.721)	(-0.104)	(0.222)	(1.288)
η_1			0.072**	0.040
			(2.854)	(1.703)
η_2			0.074**	0.031
			(2.520)	(1.391)
λ_0	0.031	0.038	0.031**	0.862**
	(1.569)	(1.926)	(3.501)	(2.908)
ρ		0.944**	0.969**	0.651**
		(4.430)	(3.683)	(6.697)
γ		0.858	0.757**	0.734**
		(3.747)**	(3.748)	(2.526)
$Q^2(12)$	14.114	250.524**	361.113**	49.658**
$Q_{\zeta_T}(12)$		38.211**	30.796**	8.975
Log-likelihood	-4358.79	-4346.11	-4335.15	-4334.21

**denotes statistically significant at 5%, numbers in parenthesis are t statistics. $Q^2(12)$ and $Q_{\zeta_T}(12)$ are the Ljung–Box Q-statistic at lag 12 for the squared standardized residuals and the jump intensity residuals respectively. μ, ϕ_1, ϕ_2 are estimates from the mean equation estimation, ω, α, β are form the GARCH equation estimation, ζ_0, ζ_1, η_0, η_1, η_2, λ_0, ρ, γ are estimates from the time varying Jumps model, and $Q^2(12)$, $Q_{\zeta_T}(12)$ are the model diagnostics parameters.

Table 15. Estimates of ARJI Models for South Africa (Non-Adjusted Return), 2001-2010

$$r_t^{adj} = \mu + \sum_{i=1}^{T} \phi_i r_{t-1}^{adj} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k}, \quad X_{t,k} \backsim N(\theta_t, \delta_t^2),$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}, \quad \lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \xi_{t-i}$$
$\theta_t = \eta_0 + \eta_1 r_{t-1} D(r_{t-1}) + \eta_2 r_{t-1}(1 - D(r_{t-1}))$, ARJI- h_t:$\delta_t^2 = \zeta_0^2 + \zeta_1 h_t$, ARJI- r_{t-1}^2:$\delta_t^2 = \zeta_0^2 + \zeta_1 r_{t-1}^2$,

Parameter	Constant	ARJI	ARJI-r_{t-1}^2	ARJI-h_t
μ	0.631**	0.190**	0.214**	0.237**
	(4.792)	(4.561)	(5.959)	(5.231)
ϕ_1	0.040**	0.0281	0.0307	0.030
	(2.302)	(1.298)	(1.356)	(0.652)
ϕ_2	-0.034	-0.051**	-0.054**	-0057**
	(-1.928)	(-2.399)	(-2.753)	(-2.718)
ω	-0.031**	0.005**	0.006**	0.007**
	(-2.643)	(2.442)	(2.262)	(4.982)
α	0.083**	0.007**	0.008**	0.010**
	(4.956)	(2.627)	(2.532)	(4.604)
β	0.882**	0.985**	0.983**	0.978**
	(3.048)	(3.484)	(3.588)	(3.226)
ζ_0	0.475**	0.818**	0.905**	0.676**
	(3.528)	(4.069)	(5.615)	(4.171)
ζ_1			0.016	0.441
			(1.117)	(1.472)
η_0	-0.205**	-0.177**	-0.322**	-0.354**
	(4.803)	(-2.995)	(-3.015)	(-4.900)
η_1			0.052	0.044**
			(1.964)	(2.308)
η_2			-0.057**	-0.063
			(-2.152)	(-1.142)
λ_0	0.970**	0.037**	0.040**	0.054**
	(3.368)	(2.172)	(2.158)	(2.262)
ρ		0.956**	0.952**	0.931**
		(4.718)	(5.552)	(5.274)
γ		0.504**	0.895**	0.943**
		(3.850)	(4.352)	(4.820)
$Q^2(12)$	124.639**	457.507**	422.461**	333.879**
$Q_{\zeta_T}(12)$		55.497**	61.497**	53.997**
Log-likelihood	-4659.95	-4650.14	-4643.56	-4641.36

**denotes statistically significant at 5%, numbers in parenthesis are *t* statistics. $Q^2(12)$ and $Q_{\zeta_T}(12)$ are the Ljung–Box Q-statistic at lag 12 for the squared standardized residuals and the jump intensity residuals respectively. μ, ϕ_1, ϕ_2 are estimates from the mean equation estimation, ω, α, β are form the GARCH equation estimation, ζ_0, ζ_1, η_0, η_1, η_2, λ_0, ρ, γ are estimates from the time varying Jumps model, and $Q^2(12)$, $Q_{\zeta_T}(12)$ are the model diagnostics parameters.

Appendix A

Time Series Graphs for Egypt Covering the Period 1st January 2001 to 31st December 2010

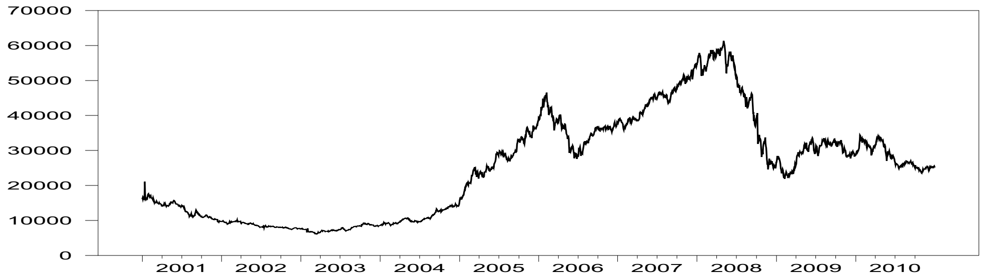

Figure 1. Total return index series (S&P BMI)

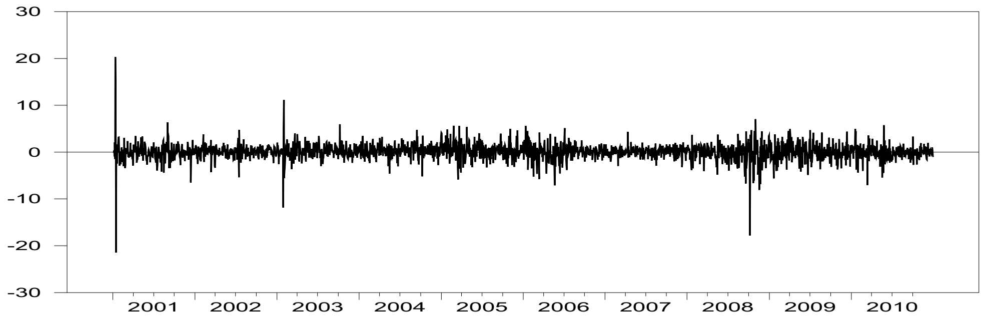

Figure 2. Return series

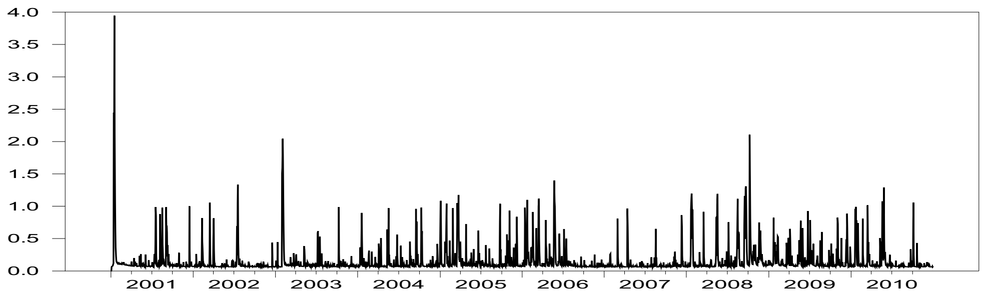

Figure 3. Jump intensity

Time Series Graphs for Nigeria Covering the Period 1st January 2001 to 31st December 2010

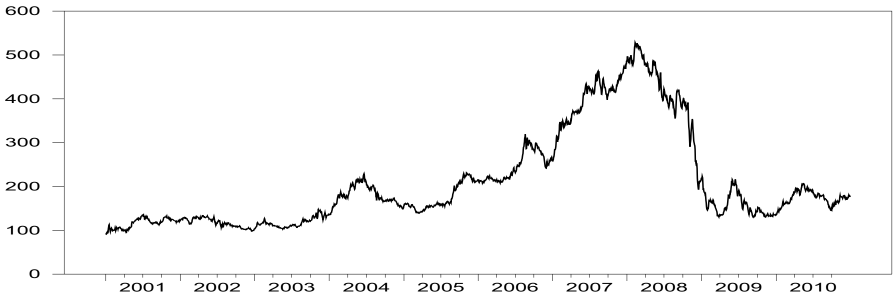

Figure 4. Total return index series (S&P BMI)

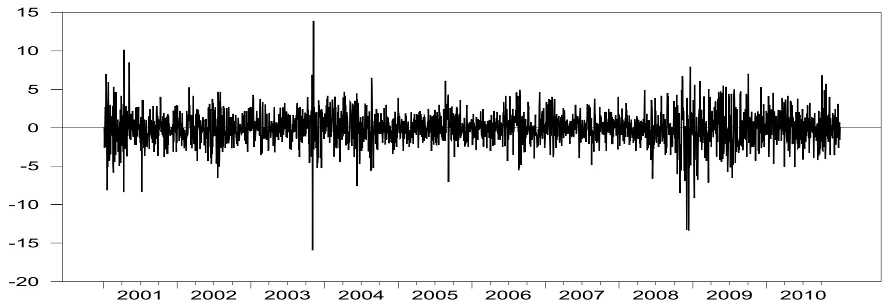

Figure 5. Return series

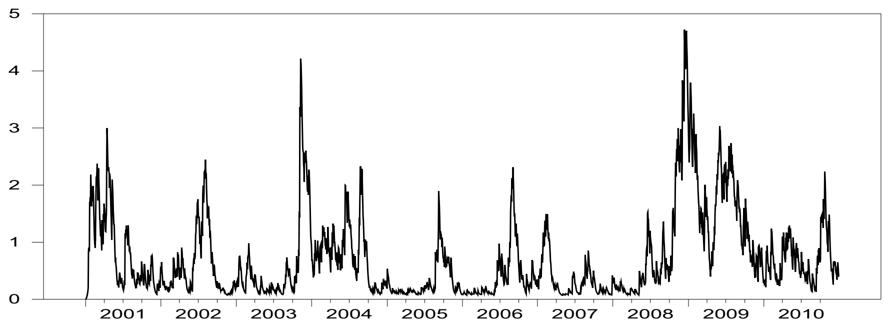

Figure 6. Jump intensity

Time Series Graphs for South Africa Covering the Period 1st January 2001 to 31st December 2010

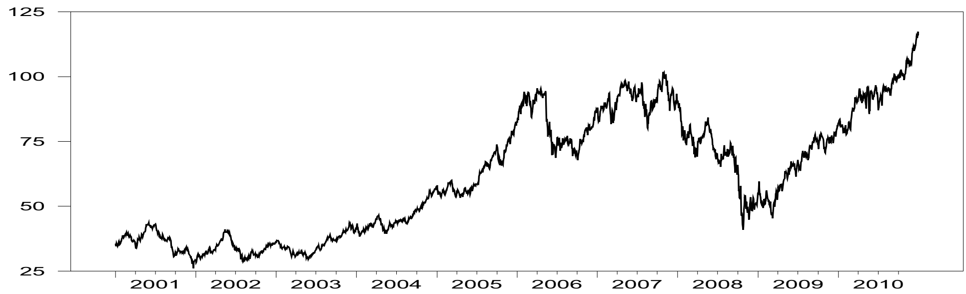

Figure 7. Total return index series (S&P IFCI)

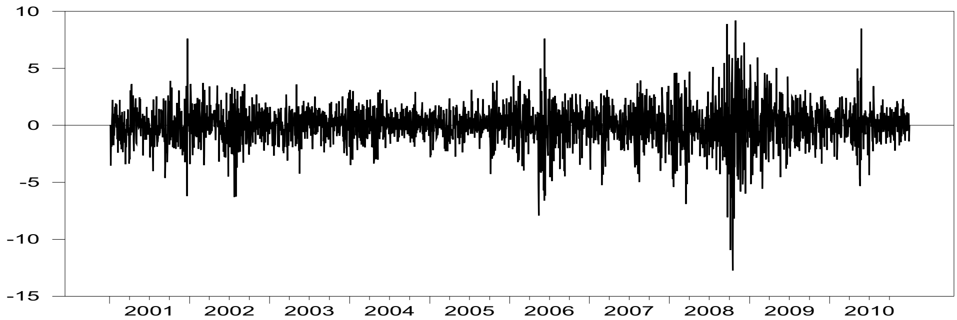

Figure 8. Return series

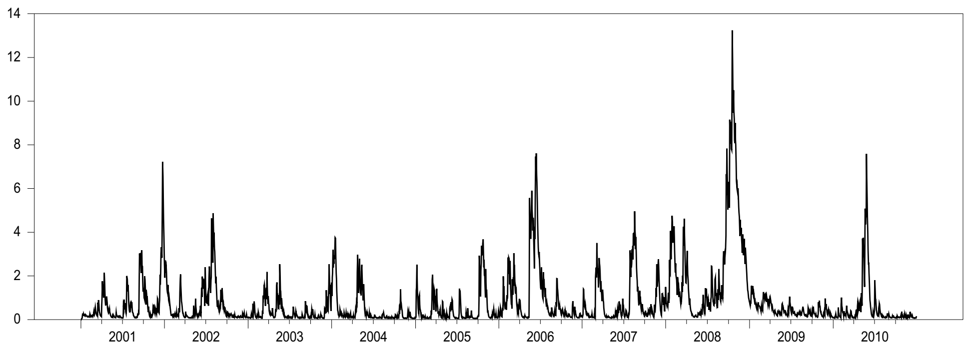

Figure 9. Jump intensity

EKONOMI OCH SAMHÄLLE
Skrifter utgivna vid Svenska handelshögskolan

ECONOMICS AND SOCIETY
Publications of the Hanken School of Economics

212. ABDIRASHID A. ISMAIL: Somali State Failure. Players, Incentives and Institutions. Helsinki 2010.

213. ANU HELKKULA: Service Experience in an Innovation Context. Helsinki 2010.

214. OLLE SAMUELSON: IT-innovationer i svenska bygg- och fastighetssektorn. En studie av förekomst och utveckling av IT under ett decennium. Helsingfors 2010.

215. JOANNA BETH SINCLAIR: A Story about a Message That was a Story. Message Form and Its Implications to Knowledge Flow. Helsinki 2010.

216. TANJA VILÉN: Being in Between. An Ethnographic Study of Opera and Dialogical Identity Construction. Helsinki 2010.

217. ASHIM KUMAR KAR: Sustainability and Mission Drift in Microfinance. Empirical Studies on Mutual Exclusion of Double Bottom Lines. Helsinki 2010.

218. HERTTA NIEMI: Managing in the "Golden Cage". An Ethnographic Study of Work, Management and Gender in Parliamentary Administration. Helsinki 2010.

219. LINDA GERKMAN: Topics in Spatial Econometrics. With Applications to House Prices. Helsinki 2010.

220. IHSAN ULLAH BADSHAH: Modeling and Forecasting Implied Volatility. Implications for Trading, Pricing, and Risk Management. Helsinki 2010.

221. HENRIK HÖGLUND: Detecting Earnings Management Using Neural Networks. Helsinki 2010.

222. KATARINA HELLÉN: A Continuation of the Happiness Success Story: Does Happiness Impact Service Quality? Helsinki 2010.

223. MARIA JAKUBIK (Maria Jakubikne Toth): Becoming to Know: Essays on Extended Epistemology of Knowledge Creation. Helsinki 2011.

224. JOHANNA GUMMERUS: Customer Value in E-Service. Conceptual Foundation and Empirical Evidence. Helsinki 2011.

225. MARIA SOLITANDER: When Sharing Becomes a Liability: An Intellectual Capital Approach to Describing the Dichotomy of Knowledge Protection versus Sharing in Intra- and Interorganizational Relationships. Helsinki 2011.

226. BEATA SEGERCRANTZ: "... The Walls Fell Down but the Blokes Just Coded...". Varieties of Stability in Software Product Development during Organizational Restructurings. Helsinki 2011.

227. ERIC BREIT: On the Discursive Construction of Corruption: A Critical Analysis of Media Texts. Helsinki 2011.

228. MICHAEL WAGNER: Inventory Routing. A Strategic Management Accounting Perspective. Helsinki 2011.

229. NIKODEMUS SOLITANDER: Designing Creativity Through Clusters: A Periodisation of Cluster Discourse. Helsinki 2011.

230. ANDREAS PERSSON: Profitable Customer Management: a Study in Retail Banking. Helsinki 2011.

231. MATHIAS HÖGLUND: Microfoundations of HRM Effects: Individual and Collective Attitudes and Performance. Helsinki 2011.

232. ANETTE SÖDERQVIST: Opportunity Exploration and Exploitation in International New Ventures. A Study of Relationships' Involvement in Early Entrepreneurial and Internationalisation Events. Helsinki 2011.

233. OSKARI LEHTONEN: An Examination of How Entrepreneurs Can Improve Their Position in Relationship to Investors. Helsinki 2011.

234. IMOH ANTAI: Operationalizing Supply Chain vs. Supply Chain Competition. Helsinki 2011.

235. DMITRI MELKUMOV: Towards Explaining the Tasks and Roles of the Boards of Directors: The Role of Contextual, Behavioural and Social Identification Factors. Helsinki 2011.

236. CHARLOTTA NIEMISTÖ: Work/Family Reconciliation: Corporate Management, Family Policies, and Gender Equality in the Finnish Context. Helsinki 2011.

237. PAUL VIIO: Strategic Sales Process Adaptation: Relationship Orientation of the Sales Process in a Business-to-Business Context. Helsinki 2011.

238. KHALID BHATTI: Factors Affecting Knowledge Sharing in Strategic Alliances: The Role of Knowledge Sharing as Strategic Control Behavior among Multinational Enterprises. Helsinki 2011.

239. STEFAN GRANQVIST: Effektutvärdering inom företagandeutbildning. Helsingfors 2011.

240. HEIKKI RANNIKKO: Early Development of New Technology-Based Firms. A Longitudinal Analysis of New Technology-Based Firms' Development from Population Level and Firm Level Perspectives. Helsinki 2012.

241. PAULINA JUNNI: Knowledge Transfer in Acquisitions: A Socio-Cultural Perspective. Helsinki 2012.

242. HENRIKA FRANCK: Ethics in Strategic Management: An Inquiry into Otherness of a Strategy Process. Helsinki 2012.

243. SEPPO LAUKKANEN: Making Sense of Ambidexterity. A Process View of the Renewing Effects of Innovation Activities in a Multinational Enterprise. Helsinki 2012.

244. MARKUS WARTIOVAARA: Values and Freedom: An Inquiry into the Rise and Fall of Billionaire Wealth. Helsinki 2012.