Studies on African Equity Markets and Global Shocks: Co-movement, Contagion, and Diversification

By

Gideon Boako

Student #: 1232452

A Doctoral Thesis Submitted in Fulfillment of the Requirements for the Award of Doctor of Philosophy Degree in the Field of Finance

The Graduate School of Business Administration, University of the Witwatersrand

Supervisor: Professor Paul Alagidede

ABSTRACT

The global financial system has experienced turmoil in the past three decades, at the least. Although the shocks originate abroad, they possess some rippling effects on African economies. The essence of market integration and cross-border listings of stocks has fueled the need for African markets to be well integrated with the global economy. Despite this need, available empirical literature exploring the integration of African markets regionally, and with the rest of the world appear unclear. Moreover, the possibility of global shocks transmitting to Africa via its emerging equity markets remains underexplored. At the same time, such knowledge is critical for not only understanding the functioning of equity markets in particular, but also important for regulating the financial system in general. This thesis addresses these gaps inherent in extant literature and proffer empirical and theoretical solutions by exploring the nexus between African stock markets and global shocks. The emphasis is on contagion, co-movement, and diversification. The thesis is organized into four empirical essays, each deeply touching on specific theme (s) that form the core of the problems or research questions under investigation while employing advanced econometric techniques that underpin the modeling of asset returns.

The first essay examines the capacity of African equity markets to act as 'hubs' for portfolio investors during tranquil and turbulent conditions of global equity and commodity markets. The findings posit that African stock markets provide decorrelation from commodity and global equity markets during extreme market conditions. To the extent that the results reveal the strength of African stocks in cushioning international portfolio investors in a mean-variance stand-point during market crashes, the essay helps to decay doubts in the minds of investors on the perceived lack of capacity of the continent's stocks to yield higher expected risk-return trade-offs during global market sell-offs. The implication of the study is that given the recent history of commodities and global stocks, fund managers around the world seeking viable alternatives to compensate for losses from commodity shocks through uncorrelated markets may consider the equity markets in Africa, albeit on account of volatility persistence, present and past market conditions, markets stability, as well as size and liquidity issues.

The second essay examines regional and global co-movement of African stock markets using the three-dimensional continuous Morlet wavelet transform methodology. The essay establishes evidence of stronger co-movements broadly narrowed to short-run fluctuations. The co-movements are time-varying and commonly non-homogeneous – *with phase difference arrow vectors implying lead-lag*

relationships. The presence of lead-lag effects and stronger co-movements at short-run fluctuations may induce arbitrage and diversification opportunities to both local and international investors with long-term investment horizons. The findings also reveal that some African equity markets are, to a degree, segmented from volatilities of the dollar and euro exchange rates.

The third essay sheds light on whether African equity markets decoupled from, and / or converged with regional and global markets from 2003 to 2014, and analyzes the implications of that for shocks spillovers. Although there is no evidence of African markets convergence either regionally or globally, shock propagation exists in a time-varying setting. Regional markets in Africa are not just 'shock absorbers' but also 'shock transmitters'.

In the last essay, the dependence structure and (extreme) downside developed equity markets and currency price risk spillover effects to African stock markets using value-at-risk (VaR) and conditional value-at-risk (CoVaR) based on stochastic copulas is modeled. The study finds evidence of non-homogenous weak negative dependence between stocks and the USD and EUR exchange rates. Except for Egypt, there is evidence of positive significant dependencies between all African markets and their developed counterparts. Although, evidence of both uni-directional and bi-directional causality, as well as upper and lower tail dependencies are found across the stocks and currency markets, only some minuscule evidence of downside spillover effects was recorded, albeit episodic. It is observed that propagation of shocks from the GFC had a second round effect in African stock markets. Thus, the impact of the GFC to African economies was not through the credit crunches and liquidity freezes in Phase I of the crisis, but rather through the global recession that followed into the second phase. The findings are consistent with the view that global shocks propagation to developing markets may stagger during crisis and intensify post-crisis. *A practical implication from the results is that given the relatively scarce resources and levels of technological know-how available to African governments, efforts to wean the continent's equity markets from adverse effects of global market crashes should be geared towards plans and programmes to mitigate the shocks not at the early stages but latter stages, where the effects to Africa could be prominently felt.*

Three key arguments are deduced from all the essays. First, although financial market underdevelopment seems *prima-facie*, to help countries isolate themselves against immediate contagion, it also reduces the ability of the real economy to cushion the impact of the crisis.

Therefore, the argument of the thesis is that despite the common fear that a highly integrated and developed market may present fertile grounds for shock spillover, Africa must continue to pursue programmes aimed at enhancing inter and intra-regional integration. However, the degree and extent of both inter- and intra-regional integration ought to be pegged at certain optimal levels in order to reap benefits from scale economies. Such endeavours at integration will not only help in risk diversification but also help smooth the impact of shocks. The second argument is that, the proposition of the "decoupling theory" i.e. returns of African equity markets and global stocks are not jointly normal during crisis periods may not be entirely tenable, empirically. Thirdly, the thesis argues that the *"shift-contagion"* theory may not reflect the reality for Africa, particularly during initial stages of crisis. Instead, the thesis suggests an extension and argues for a *"delayed-shift contagion"* theory.

Keywords: Decoupling, shift-contagion, spillover effects, CoVaR, exchange rates, commodities.
JEL Classification: C40, C58, F31, F36, G10, G11, G15,

LIST OF PUBLICATIONS AND OUTPUTS

Prior to submission, portions of the thesis have been published in the following peer reviewed journals and working papers while some others are under submission.

Peer-reviewed Journal Publications

1. Boako, G., and Alagidede, P., (2016). Global commodities and African stocks: A "market of one"? *International Review of Financial Analysis,* 44: 226-237.
2. Boako, G., Omane-Adjepong, M., Frimpong, J.M., (2016). Stock returns and exchange rate nexus in Ghana: a Bayesian quantile regression approach. *South African Journal of Economics,* 84 (1): 149-179.
3. Boako, G., and Alagidede, P., (2016). African stock markets convergence: Regional and global analysis. *Finance Research Letters, 18: 317-321.*
4. Boako, G., and Alagidede, P., (2016). Should Africa's emerging markets still be considered as a separate asset class? *Applied Economics Letters, 24(1): 61-66.*

Working Paper Publication

1. Boako, G., and Alagidede, P., (2015). Global commodities and African stocks: Insights for hedging and diversification strategies. *Economic Research Southern Africa (ECONRSA) Working Paper* 569: 1-30. http://www.econrsa.org/publications/working-papers/global-commodities-and-african-stocks-insights-hedging-and
2. Boako, G., Alagidede, P., (2016). Regionalization versus Internationalization of African Stock Markets: A frequency-time domain Analysis. *Economic Research Southern Africa Working Paper* 642: 1-41.

Book Chapter

1. Boako, G., and Alagidede, P., The stock market development and economic growth puzzle: Empirical evidence from Africa. *Palgrave McMillan (forthcoming).*

Papers under Review

1. Boako, G., and Alagidede, P. Co-movement of Africa's equity markets: Regional and global analysis in the frequency-time domains. *Physica A: Statistical Menchanics and Applications.*
2. Boako, G., and Alagidede P. Currency price risk and stock markets in Africa: Dependence and downside spillover effects with stochastic copulas. *Journal of Empirical Finance.*
3. Boako, G., and Alagidede, P. Downside price movements across financial markets: A CoVaR-copula approach. *Journal of International Money and Finance.*

4. Boako, G., and Alagidede, P. African stock markets in the midst of the global financial crisis: Recoupling or decoupling? *Empirical Economics.*
5. Boako, G., and Alagidede, P. African equities, global factors and cross-market nexus: Implications for diversification and risk reduction. *Investments Analyst Journal.*
6. Boako, G., and Alagidede, P. Examining evidence of 'shift-contagion' in African stock markets: A CoVaR-copula analysis. *International Review of Economics and Finance.*

Conferences

1. Boako, G., Omane-Adjepong, M., Frimpong, J.M. Stock returns and exchange rate nexus in Ghana: a Bayesian quantile regression approach. *In the Proceedings of the 12TH African Finance Journal Conference, President Protea Hotel – Cape Town, South Africa 21-22 May, 2015.*
2. Boako, G., Alagidede, P. Hedges and safe havens: An examination of African stocks and global economic factors. *IJAS Economics and Finance Conference, University of London (UK)* and also *2nd Biennial Conference of the Economic Society of South Africa, University of Cape Town 2 to 4 September, 2015 (2-4 September, 2015).*
3. Boako, G., Alagidede, P. Co-Movement between Africa and international stock markets: Time-varying conditional correlations with wavelet analysis. *IJAS Economics and Finance Conference, University of London (UK) and also, 2nd Biennial Conference of the Economic Society of South Africa, University of Cape Town 2 to 4 September, 2015 (2-4 September, 2015).*
4. Boako, G., Alagidede, P. Exploring Africa's relative potential of possessing hedging or safe haven characteristics for international portfolio investors. *AIB Conference, Gordon Institute of Business, University of Pretoria, Johannesburg, 25-28 August, 2015.*
5. Boako, G., and Alagidede, P. African stock markets in the midst of the global financial crisis: Recoupling or decoupling? *African Review of Economics and Finance Conference, August 11 to 12, 2016, KNUST, Kumasi, Ghana.*
6. Boako, G., and Alagidede P. Currency price risk and stock markets in Africa: Dependence and downside spillover effects with stochastic copulas. *African Review of Economics and Finance Conference, August 11 to 12, 2016, KNUST, Kumasi, Ghana.*

DECLARATION

I, **Gideon Boako**, hereby declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in fulfillment of the requirements for the award of Doctor of Philosophy degree in the field of Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Gideon Boako

Signed at …………***Wits Business School (WBS)***………………………………………

On the ……***20***th ……………….. day of ……***October***……………………….. ***2016***

DEDICATION

To Jodi Agyeiwaa Boako & Stefan Nana Asare Boako

ACKNOWLEDGEMENT

The Ph.D. journey was sometimes both tough and rough but the divine presence and favour of God made it possible. I am most grateful to the Almighty God for a successful completion of the Ph.D. journey. I could not have humanly made it this far without the unflinching support of many people, who deserve to be acknowledged. It is an obligation to express my profound appreciation to Prof. Paul Alagidede (my supervisor) for his support, tutelage, and brotherly love during my doctoral studies. Prof., your perfect coaching enabled me to create a text that is current, accurate, unique, and modern in its approach. Prof., words cannot be exhaustive of the kind of gratitude I wish to show to you. In sum, I say may the mercies and favour of the Lord that surpass all understanding be your portion. I cannot thank you and leave your adorable and all-smiling wife, Dr. (Mrs.) Ann Alagidede. May God bountifully bless her and her generations. In fact, the journey started from somewhere. In that sense, I extend my sincere gratitude to Prof. Joseph Magnus Frimpong (Finance Professor and former Dean, Kwame Nkrumah University of Science and Technology – KNUST School of Business), who also doubled as my MBA and MPhil thesis supervisor for discovering the seed of excellence in me and bringing me to light in appreciation of the Finance and Economics fields. Further, I am deeply indebted to Prof. Joshua Y. Abor (Professor of Finance and Dean - University of Ghana Business School). Prof., I reckon vividly how you spoke favourably about my MPhil thesis at KNUST when you were the external examiner at my viva and got the panel of examiners to recommend me for Ph.D. True to your words, you followed up on me months later and took the pain to secure me admission at Wits Business School by introducing me to Prof. Alagidede. If today I am part of the 'club' of Ph.D. holders in Finance, you are one of the reasons. May God richly bless you. Thanks are also extended to the following academics who either sat on my Ph.D. panels or offered words of encouragement, useful comments, and direction towards the doctoral journey: Prof. Kalu Ojah (Professor of Finance and Director of Masters in Finance and Investment programme at Wits Business School), Prof. Eric Schaling (Professor and Jelle Zijlstra Chair of International Finance, Wits Business School), Prof. Nicholas Biekpe (Professor of Development Finance and Econometrics, Graduate School of Business, University of Cape Town), Dr. Christopher Odongo Kodongo (Ph.D. Director, Wits Business School), Prof. Gregory John Lee (Professor, Wits Business School), Dr. George Adu (Senior Lecturer, Kwame Nkrumah University of Science and Technology), Prof. Samuel Azazu and Dr. Kolawole Ijasan (University of the Witwatersrand School of Construction Economics), and Prof. K.A Osei (University of Ghana Business School). Thanks go to Mrs. Mmabatho Leeuw and all administrative staff, as well as, colleagues in the Ph.D. office at the Wits Business School (notably, Euphy, Chengette, Grace, Godfred, Tetyana, Numusa, Dr. Jones, etc). Additionally, I am exceedingly grateful to the following personalities for their various forms of assistances towards my Ph.D.: Nana Addo Dankwa Akufo-Addo (Flagbearer of the New Patriotic Party (NPP) 2016, Ghana), Dr. Alhaji Mahamudu Bawumia (Running mate to the Flagbearer of NPP, 2016), Hon. Osei-Kyei Mensah Bonsu (Minority Leader, Parliament of Ghana), Mr. George Ayisi-Boateng, Mr. Gabby Asare-Otchere Darko, Ashanti Regional Minority Caucus in Parliament, Hon. Dr. Anthony Akoto-Osei (Member of Parliament, Old Tafo Constituency, Ghana), Mr. Asare Yeboah, H.E Hon. Isaac Osei (Member of Parliament, Subin Constituency, Ghana), and Hon. Dr. Mark Assibey-Yeboah (Member of Parliament, New Juabeng South Constituency, Ghana). I also appreciate the support of colleagues at KNUST School of Business and staff and management of Garden City University College, Kumasi (particularly Mr. Albert Acquah and Dr. Wilhelmina Donkor). Efforts by friends such as Maurice Omane-Adjepong, Bejamin Wadie-Peprah, Festus Adu-Attafua, JB, Ridwan Issah Khalifah, Beatrice Osei, Eugene Ofori-Appiah, Kwame Peprah Boaittey, James Owusu, Ameyaw Martin, Denis Kwakwa, Dr. Kingsley Nyarko, and Phylis Obeng are duly acknowledged. I also acknowledge financial assistance offered by the following bodies: the University of Witwatersrand through the award of the Ph.D. Postgraduate Merit Award and Research/Teaching Assistantship award; South African National Research Foundation (NRF) through the Competitive Programme for Rated Researchers Scholarship Award; UK/South Africa Newton Fund Travel Grant, and Southern African Trust/Wits Business School Research Associate to Chair in African Philanthropy Award. To my family (my dear wife - Pamela, mother, and siblings,), friends, critics, as well as anyone worth mentioning who I have not specifically acknowledged, I say, “Me daa se” – to wit, “thank you”. The usual caveat applies.

TABLE OF CONTENTS

Abstract		ii
List of Publications and Outputs		v
Declaration		vii
Dedication		viii
Acknowledgement		ix
Table of Contents		xi
List of Tables		xv
List of Figures		xvii
List of Abbreviations		xviii
CHAPTER ONE		
Introduction		
1.	**Background to the study**	**1**
1.1	**Objectives of the thesis**	**2**
1.2	**Significance of the thesis**	**2**
1.3	**Structure of the thesis**	**4**
	References	**10**
CHAPTER TWO		
African Stock Markets: A Hub for International Portfolio Diversification?		
2.	**Introduction**	**12**
2.1	**Overview of stock markets development in Africa**	**14**
2.2	**Review of related studies**	**17**
2.3	**Data and research design**	**25**
2.3.1	*Data*	**25**
2.3.2	*The extended market model*	**27**
2.3.3	*Modeling dynamic conditional correlation (DCC)*	**28**
2.3.4	*Econometric approach to the hedging and diversification analysis*	**29**
2.4	**Empirical results**	**31**
2.4.1	*Preliminary analysis*	**31**

2.4.2 The excess market model analysis **35**

2.4.3 African markets correlations with commodities and world markets **39**

2.4.4 Optimal hedge ratios (OHR) and portfolio weights of African stocks **48**

2.4.5 Analysis of the hedging and diversification hypothesis **52**

2.4.6 Mean-variance portfolio selection and optimization with stocks in Africa **54**

2.5 Conclusion **60**

References **61**

Appendix 1A: **68**

CHAPTER THREE

Co-Movement of Africa's Equity Markets: Regional and Global Analysis in the Frequency-Time Domains

3. Introduction **69**

3.1 Research design **73**

3.1.1 The continuous Morlet wavelet transforms 73

3.2 Data and baseline analysis **75**

3.3 Empirical results of the wavelet power spectrum, coherency, and phase difference **82**

3.3.1 Analysis of global co-movements **87**

3.3.2 Evidence from regional markets in Africa **96**

3.3.3 Co-movements with exchange rates **101**

3.4 Conclusion **105**

References **106**

Appendix **110**

CHAPTER FOUR

Regionalization vs. Internationalization of African Stock Markets: Decoupling and Convergence

4. Introduction **111**

4.1 The decoupling phenomenon **114**

4.2 Research design **116**

4.2.1 The 'market convergence hypothesis' – MCH **116**

4.2.2 Econometric approach to the MCH: BTP spectral density test **118**
4.2.3 Modeling decoupling and the implications for shocks spillover **121**
4.2.3.1 The empirical framework **121**
4.3 Data and preliminary analysis 123
4.4. Empirical results and discussion 127
4.4.1 Results of the 'Market Convergence Hypothesis – MCH' **128**
4.4.2 Analyzing decoupling and spill-over effects **128**
4.4.3 Spillovers from regional and global markets **132**
4.4.4 Joint regional and global spillovers **137**
4.5 Conclusion 140
References 141
Appendix **145**

CHAPTER FIVE

Spillover Effects, Financial Contagion, and Market Interdependence

5. Introduction 154
5.1 Literature survey 158
5.1.1 The stock - foreign exchange rate market nexus – theory and empirics **158**
5.1.2 Empirics on contagion and markets interdependence **160**
5.1.3 Theoretical literature - contagion and/or interdependence **163**
5.1.4 Contagion transmission pathways **165**
5.2 Data and empirical strategies 168
5.2.1 Data **168**
5.2.2 Modelling dependence using Copulas **169**
5.2.3 The interdependence estimator **174**
5.2.4 Estimating spillovers with CoVaR-copula **176**
5.3 Empirical results and discussion 180
5.3.1 Baseline results **180**
5.3.2 Marginal model results **185**
5.3.3 Empirical evidence on dependence using Copulas **185**
5.3.3.1 African stock and exchange rate markets **191**
5.3.3.2 African and developed stock markets **200**

5.3.4 Toda Yamamotto (T-Y) model test results for interdependence **214**

5.3.5 Exchange rates and developed markets spillover effects to African stock returns **218**

5.3.6 Are there evidences of 'shift-contagion' in African stock markets? **225**

5.4 Conclusion **237**

References **240**

LIST OF TABLES

Table 2.0: Indicators of capital market development in SSA and the rest of the world **16**

Table 2.1: Institutional, operational, and infrastructural development characteristics of African stock markets as at end of 2014. **18**

Table 2.2: Summary statistics of daily returns **32**

Table 2.3: Assets behaviour in falling commodity and global markets **35**

Table 2.4: Estimation results of the static market model and risk-adjusted performance measures **38**

Table 2.5: Augmented market model results (full sample period) **41**

Table 2.6: Dynamic conditional correlation results (*full sample period*) **42**

Table 2.7: Dynamic conditional correlation results *(Sub-sample period)* **44**

Table 2.8: Optimal portfolio weights, hedge effectiveness and ratios for Africa's equities and Commodities **51**

Table 2.9: Results of hedge and diversification assessments using contemporaneous returns **55**

Table 3.0A: Descriptive statistics of returns (in volatilities) **78**

Table 3.0B: Summary statistics of bilateral exchange rates expressed in Euros (€) and US Dollars ($) **79**

Table 3.1: Correlations of markets with bilateral exchange rates **83**

Table 3.2: Correlations of volatility of returns **44**

Table 4.0: Unit root test **127**

Table 4.1: Summary statistics of volatility of returns **130**

Table 4.2: Contemporaneous correlations of volatilities **134**

Table 4.3a: Estimated coefficients of regional and global shocks **136**

Table 4.3b: Estimated coefficients of joint regional and global shocks **139**

Table 5.0: Financial market contagion transmission pathways **168**

Table 5.1: Copula specifications **173**

Table 5.2: Summary statistics **186**

Table 5.3: Parameter estimates for marginal models of domestic currency against EUR **188**

Table 5.4: Parameter estimates for marginal models of domestic currency against USD **189**

Table 5.5: Parameter estimates for marginal models of stock markets **190**

Table 5.6: Bivariate copula model estimates for African stock market and USD **192**

Table 5.7: Bivariate copula model estimates for African stock market and EUR **197**

Table 5.8: Bivariate copula model estimates for African stock market and Asia ex-J **202**

Table 5.9: Bivariate copula model estimates for African stock market and EUSTXX **203**

Table 5.10: Bivariate copula model estimates for African stock market and FTSE100 **204**

Table 5.11: Bivariate copula model estimates for African stock market and S&P500 **205**

Table 5.12: Toda-Yamamoto causality test results and diagnostics **215**

Table 5.13: Descriptive statistics and tests for downside value-at-risk (VaR) and conditional value-at-risk (CoVaR) for African stock returns **217**

Table 5.14: Best-fit (optimal) copula selection – full sample **229**

Table 5.15: Descriptive statistics and tests for shift-contagion in African stock returns using downside CoVaR **232**

LIST OF FIGURES

Figure 2.0: Time plots of all returns series **34**

Figure 2.1: Performances of African stocks-commodity portfolios mix **60**

Figure 3.0: Daily volatility changes in country and regional stock markets in Africa as well as global market indices **80**

Figure 3.1: Detection of multiple structural shocks (changes) with BIC **81**

Figure 3.2. Wavelet power spectrum of the volatilities **87**

Figure 3.3: Cross-wavelet squared coherency and phase difference plots between the African stock markets and MSCI-DW, MSCI-EM, and BCOM **91**

Figure 3.4: Cross-wavelet squared coherency and phase difference plots between volatilities of individual Africa's stock markets and regional stock markets **100**

Figure 3.5: Cross-wavelet squared coherency and phase difference plots between Africa's stock markets US dollars and Euro **104**

Figure 4.0: Plots of volatilities of returns **129**

Figure 5.0a: Time series plots of weekly stock market indices and exchange rates **182**

Figure 5.0b: Time series plots of weekly stock market indices (Africa and developed) **184**

Figure 5.1: Normal *qq* plots of all returns **187**

Figure 5.2: Plots for parameter estimates of time-varying copulas between African stock markets exchange rate returns **195**

Figure 5.3: Time paths for time-varying dependence parameters between African and developed stock markets returns **213**

Figure 5.4: Downside value-at-risk (VaR) and conditional value-at-risk (CoVaR) for African stock market returns **225**

Figure 5.5: Downside conditional value-at-risk (CoVaR) for African stock market returns **231**

LIST OF ABBREVIATIONS

Abbreviation	***Meaning***
ADF	Augmented Dickey-Fuller
ADR	American Depository Receipts
AfDB	African Development Bank
AFSTOCKs	African Stocks
AIC	Alkaike Information Criterion
ARCH	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving Average
ASEA	African Securities Exchanges Association
BCOM	Bloomberg Commodity Index
B-G	Breusch-Godfrey
BIC	Bayesian Information Criterion
BRICS	Brazil, Rusia, India, China, and South Africa
BTP	Bartlett, Tukey, and Parzen
CAD	Canadian Dollar
CAPM	Capital Asset Pricing Model
CDF	Conditional Distribution Function
CDS	Credit Default Swap
CFTC	Commodities Futures Trading Commission
CI	Composite Index
CI	Confidence Interval
CoVaR	Conditional Value-at-Risk
CUSUM	Cumulative Sum
CWT	Continuous Wavelet Transform
D	Dummy
DCC	Dynamic Conditional Correlation
DDM	Dividend Discount Model
DM	Domestic Market
DWT	Discrete Wavelet Transform
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
EIA	Energy Information Administration

EU	Eurozone
EUR	Euro (**€)**
FDI	Foreign Direct Investment
FER	Foreign Exchange Rate
FM	Financial Market
FR	Forbes and Rigobon
FX	Foreign Exchange
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GC	Global Commodities
GDH	Gradual Diffusion Hypothesis
GDP	Gross Domestic Index
GED	Generalized Error Distribution
GEV	Global Economic Variable
GFC	Global Financial Crisis
GSE	Ghana Stock Exchange
HE	Hedge Effectiveness
ICAPM	International Capital Asset Pricing Model
ICH	Income Convergence Hypothesis
IFC	International Financial Corporation
IMF	International Monetary Fund
IR	Information Ratio
JALSH	Johannesburg All-Share-Index
JB	Jacque-Bera
JSE	Johannesburg Stock Exchange
K-S	Kolmogorov Smirnoff
LDM	Licensed Dealing Member
LM	Lagrange Multiplier
ln	Natural Logarithm
MA	Moving Average
MAEC	Macroeconomic Variable
MAX	Maximum
MEM	Multiplicative Error Fully-Interdependent Model

MIN	Minimum
MSCI-DW	Morgan Stanley Capital International Developed Markets Index
MSCI-EM	Morgan Stanley Capital International Emerging Markets Index
MSCI-W	Morgan Stanley Capital International World Index
M-V	Mean-Variance
NA	Not Available
NAFM	Non-African Financial Market
OECD	Organization of Economic Corporation and Development
OG	Oil and Gold
OHR	Optimal Hedge Ratio
OLS	Ordinary Least Squares
OPEC	Organization of the Petroleum Exporting Countries
PCF	Private Capital Flow
REC	Regional Economic Communities
S&P500	Standard and Poor 500 Index
SD	Standard Deviation
SFGC	Standard F-type Granger Causality
sg	stock-gold
SJC	Symmetrized Joe-Clayton
so	stock-oil
SR	Sharpe Ratio
SSA	Sub-Saharan Africa
TGARCH	Threshold Generalized Autoregressive Conditional Heteroscedasticity
TR	Tracking Error
TVP	Time-Varying Parameter
T-Y	Toda Yamamoto
UEP	Uncovered Equity Parity
UK	United Kingdom
UNDP	United Nations Development Programme
US	United States
USD	United States Dollar (**$**)

VaR	Value-at-Risk
Var	Variance
VAR	Vector-Autoregressive
WCPS	Wavelet Cross Power Spectrum
WDI	World Development Indicators
WFE	World Federation of Exchanges
WPS	Wavelet Power Spectrum
XWT	Cross Wavelet Transform
ZA	Zivot and Andrews

CHAPTER ONE

Introduction

1. Background to the thesis

The connectedness between developed and emerging economies remains a critical factor to the development and modernization of the global economy. Critical metrics for independence, among others, are stock market integration, harmonization of trade, and legal and regulatory mechanisms. Recent economic and financial developments have re-ignited the need to re-assess emerging economies independence and self-sufficiency levels (Claessens *et al.,* 2010) in the broader context of the global economy. Africa's financial markets have shown significant fluctuations in tandem with performance of the global economy. Following the mid-2012 upswings in the world equity markets, stock markets in Africa made significant strides, notwithstanding divergences across sub-regions. A report by the African Development Bank, AfDB (2013) shows that despite the continuous recovery and substantial gains by the North African markets, specifically Tunisia and Egypt, Morocco's exposure to the Eurozone's economic crunch saw the latter's bourse fall by 14.5 per cent in value by the end of 2012. Despite the minor fall in May 2012, the South Africa FTSE/JSE All-Share Index (JALSH) rose by 12.7 per cent from December 2011 to September 2012. In West Africa, the Ghanaian bourse in 2013 witnessed momentous growths in stocks as the Composite Index (CI)[1] increased by 78.8 per cent between 2010 and 2013. In U.S dollar ($) terms the CI went up by 55 per cent, second only to Malawi in Africa.[2]

During the last two decades, the Sub-Saharan African (SSA) region has experienced growth in the number of stock exchanges. In all, 29 exchanges have been recorded (Ntim, 2012). Though relatively nascent, the growing number of equity markets offers meaningful opportunities for the integration of Africa into the global financial markets and attracts investments and capital (AfDB, 2013). Financial market integration has the possible effect of surging cross-border listings of stocks, and amplifying the transmission of shocks with consequences for the domestic and global economy. Evidence of shock transmission and market interdependence could also have meaningful

---

[1] CI is the Ghana Stock Exchange (GSE) market based capitalization index with a base date and base index value of 31-12-10 and 1,000 respectively.

[2] African economies have been growing more rapidly and witnessing accelerated integration with most economies in the area of trade and investments. Africa covers 20.4% of the world's land area, remains the second largest and second most populous continent in the world (covering 15% of the world's human population, after Asia; and provides substantial contribution to the global gross domestic product (GDP). The current promising expansion of the African economy has useful inferences for the growth of their equity market and their financial interrelations with the global market.

suggestions for trading strategies, hedging and financial market regulations (Berkiros, 2014). Establishing market interdependence and integration may be useful for the achievement of gains for portfolio balancing and risk reduction (Alagidede, 2008; Berkiros, 2014).

From the foregoing, it can be inferred that the ability of stock markets to fulfill their roles in hedging (example inflation and exchange rate risk), reducing systematic market risk, and improving trading strategies is anchored on how well the markets are able to respond to external shocks and their level of co-movement and interdependence. Failure to establish empirically the level of co-movement, and interdependence of African equity markets with the global economy may have severe implications. First, it may present problems of sub-optimal allocation of assets with the attendant ramifications for economic growth, and risk prevention and control. The second problem is that, in a situation of severe global economic meltdown, such as the 2007-2009 U.S sub-prime mortgage crisis, contagion, *en-route* the equity markets to the African economy may be unnoticed. The consequences of this may be dire, and in extreme situations insurmountable in the short term.

1.1 Objectives of the thesis

The thesis focuses on the dynamic linkages between African equity markets and the global financial system with particular emphasis on co-movement, contagion, interdependence, and diversification. Particularly, it aims at finding out the extent of dependence and shocks spill-over between African equity markets and the global economy - *symmetry versus asymmetry*. Further, attempt is made to examine how African markets inter-relate internationally and regionally. Moreover, of particular significance in the studies are the African markets – global shocks nexus, and the implications of the said nexus for professional fund managers, policy makers, regulators, and academic research.

1.2 Significance of the thesis

The anticipated contribution to extant literature underscores the significance and justification for conducting this research. The first contribution is exemplified as we address the paucity of studies that have empirically investigated, within the particular context of Africa contagion of shocks, co-movement, and interdependence of financial markets. Precisely, this thesis conducts an empirical assessment of the "decoupling" theory, which addresses the issue of whether or not African markets are immune to global shocks, and if not, are the transmissions asymmetrical or symmetrical. Of great significance is the specification of the theoretical framework for the contagion theory. The specification of the model is ideal since it encapsulates the various phases of the 2007-2009 global financial crisis and draws important implications for policy makers and investors. The modeling also helps us to examine shocks or spillover effects at the (extreme) downside market conditions using both conditional value-at-risk (CoVaR) and value-at-risk (VaR) based on copulas. This provides a unique contribution to the modeling of spillover effects within the stock market literature.

The second contribution is that, converse to existing studies that use data periods capturing few phases of the 2007-2009 global financial crisis (GFC), this thesis uses current and suitable data sets to investigate the market co-movement, contagion and interdependence between African markets and global shocks. This handles the problems inherent in the dearth of extant literature which use data sets that capture crisis periods that long predate the GFC. Additionally, most studies use data on only stock markets to examine co-movement, contagion, and/or interdependence. The challenge associated with this is that, in non- integrated and undiversified markets, effects of price changes in the global markets may be rarely noticed. Hence, the reliance on only stock markets' data-sets to model co-movement, contagion, or interdependence may be misleading or provide inconsistent results. The thesis partly addresses this concern by focusing on African markets that are theorized to be integrated/not integrated, and diversified/undiversified. Also, we include in the structure some global economic variables such as gold, cocoa, platinum, silver, and crude oil that are determined outside the territory of the equity market framework. By this, it is expected that contagion may be detected even when the equity markets are not integrated. Thus, we are able to distinctively model shocks emanating from global equity markets, commodities, and exchange rates.

The novelty of this research is also exemplified in the methodologies employed. Most importantly, the use of different econometric and estimation techniques which have relatively not seen substantial application on the African markets constitute a significant advancement in the empirical studies on African stock markets and global shocks. Altering the methodological approach in related studies has the significant consequences of producing relevantly new robust results.

In all, it is expected that this thesis will offer deeper insights into how well to integrate the African financial system to avert the problems of financial shock contagion. Knowing the nature of spillover effects to African equity markets will inform policy decisions aimed at curbing future occurrences. On the theoretical front, we extend the definition on contagion to include the "delayed shift-contagion" phenomenon. It is the optimism of this thesis to inspire other researchers, especially in Africa to develop a renewed penchant to research extensively in this area.

1.3 Structure of the thesis

In all, the contributions of the thesis to literature are organized in four empirical chapters. In the following paragraphs, Chapters 2 – 5 are summarized, in turn highlighting briefly on methodologies, key findings, and contributions to the literature. Note that only brief summaries are provided and therefore interested readers are encouraged to read the details from the main appended chapters.

Chapter Two: Owing to frequent fluctuations in global markets, diversifying across emerging markets is increasingly becoming a necessity. Despite this, a cloud of uncertainty surrounds the relative capacities of emerging markets to provide the required shields for international investors, especially during extreme market conditions. Meanwhile, on account of the "decoupling" proposition that emerging markets' stock returns are not jointly normal with that of developed markets during crisis, it is anticipated that crashes in the world markets may not instantaneously affect returns from emerging markets making them sustainable hubs for diversification. In this chapter, we explore the relative potentials of African equities to provide opportunities for hedging and diversification for global investors by employing a battery of methodologies to data of daily periodicity on close-to-close basis from January 3, 2003 to December 29, 2014. This chapter fills important gaps in the literature by first, synthesizing the dynamic relationship between stocks and commodities from the perspectives of investors' already holding positions in the commodities markets, and the implications of such nexus for diversification and hedging. Secondly, the chapter provides useful empirical evidence to augment efforts of policy makers at promoting Africa as a hub for certain kinds of international investments.

The analyses in this chapter are done in stages. First, we examine risk-return trade-offs of portfolio investments in the African markets by specifying an extension of the capital asset pricing model (CAPM) in a static framework using global indices such as the Morgan Stanley Capital International World (MSCI-W), the Standard and Poor 500 (S&P 500), and the Bloomberg commodities (BCOM), as global benchmarks. We estimate this model to determine the global index that exerts the highest influence on Africa's unexpected average excess returns on risk-adjusted basis in the full-sample and post-GFC periods. Moreover, tracking errors (TRs) and information ratios (IRs) of each

African market, relative to the global benchmarks are computed to augment the analysis of the risk-adjusted performances. To be able to capture the impact of the global commodities (GC) on the African stocks on risk-adjusted basis, an augmented version of the CAPM is specified. In the second stage, we estimate the evolution of time-varying conditional correlations between African stocks and the commodities and benchmark markets (hereafter referred to as global factors) across the entire distribution of the two markets and with consideration to the recent global financial crisis (GFC). We examine how the crisis has influenced correlation and the bearing of that on Africa's markets relative capacities to act as potential hedges and diversifiers. Next we estimate hedge ratios, optimal portfolio weights and effectiveness of all possible stock- global factors hedges. The optimal hedge ratio assists us in determining the dollar amount of a global factor that the hedger must short for each long position taken in an African stock; while the portfolio weight measures the optimal holding weight of an African stock in a $1 portfolio of stock-global factor at a time.

Further, we are interested in finding out whether declining moments in stock and global factors propel international portfolio investors to consider African stocks as safe destinations for their investments. Intuitively, following the rather weak level of integration between African stocks and the global financial environment, there is the possibility of Africa's decoupling from global shock contagion leading to lower or negative cross-assets correlation between Africa and the international markets. For this reason, we analyze the "hedge/diversifier" hypothesis to examine whether African stocks can act as diversifiers and hedges in extreme conditions of the global markets. In addition to these, we examine within the mean variance portfolio optimization framework, the best portfolio combinations that will optimize returns whilst reducing variances.

The findings indicate the presence of non-linear relationships between some African stocks and returns on global commodities. Thus, global commodity market investors react differently towards investment potentials in African stocks during tranquil and crisis periods. Additionally, from the mean–variance standpoint, we observe that including African equities in a diversified portfolio has the effect of lowering risk whiles simultaneously increasing expected returns. However, any such investment strategies may have to be informed by volatility persistence, as well as past and present market conditions.

Chapter Three models time-varying co-movement of African stock markets regionally and globally. Using data of daily periodicity, we apply the three-dimensional continuous Morlet wavelet technique to examine co-movement of African stock markets. The analyses which are done in segments investigate co-movements with global markets; bilateral exchange rates expressed in US dollars and euro; and four regional markets in Africa. Particularly, the following questions are investigated: What have been the nature and extent of African stock markets co-movement, regionally and globally around the GFC? Were Africa's stock markets co-movement pathways influenced by the 2007-2009 GFC? Does the co-movement hold any relevant implications for diversification?

To answer these questions, the investigations in this chapter are done in stages. It is important to stress that, converse to earlier studies (for example, Alagidede, 2008; Forbes and Rigobon, 2002; and Ntim, 2012) which largely analyzed stock returns co-movement; we examine the co-movement of equity markets volatilities. The rationale is that volatility quantifies the risk of a stock market, and therefore, it is relevant to portfolio managers when rebalancing their portfolios from one market to another (Garham and Nikkinen, 2011). This logic is more grounded following the advent of the GFC that heightened market uncertainties and price fluctuations. The results therefore provide risk managers and policy makers with deeper comprehension of equity markets dynamics across geographical regions, thus helping them in devising effective hedging and diversification strategies. This makes our results robust to existing ones on African markets co-movement.

In the empirical analysis, we first examine the volatility dynamics and presence of multiple structural changes of all variables to determine how stable each variable was throughout the sample period using the Bayesian Information Criterion (BIC) in Zeileis *et al.,* (2003). In the next stage, we employe the three-dimensional continuous Morlet wavelet (i.e. wavelet power spectrum, coherency, and phase difference) transform to examine the time-varying co-movement of equity markets in Africa. The wavelet analysis helps in the localization in the frequency and time domains, has the ability to breakdown any ex-post variables on different frequencies to examine the subtleties of joint movements across diverse time horizons without losses in information, and also provides a better trade-off between detecting oscillations and peaks or discontinuities. The method also simultaneously allows for assessment of the impact of investment horizon. From the point of view of portfolio diversification, short-term or long-term investors are more concerned with the co-movements at higher or lower frequencies to help them formulate their investments strategies. Thus, through wavelets we are able to make distinction between the short-term and long term investor, as well as their investments horizons.

We find evidence of stronger co-movements of the African stock markets broadly narrowed to short-run fluctuations. The co-movements are time-varying and commonly non-homogeneous – *with phase difference arrow vectors implying lead-lag relationships*. The presence of lead-lag effects and stronger co-movements at short-run fluctuations may induce arbitrage and diversification opportunities to both local and international investors with long-term investment horizons. The findings also reveal that some African equity markets are, to a degree, segmented from volatilities of the dollar and euro exchange rates. Another implication of our finding is that, from the perspective of the international investor, equity portfolio diversification opportunities into African markets (specifically, Tunisia, South Africa, Nigeria, Kenya, Egypt, and Botswana) are relatively less significant in the short term than the long term. International investors with long-term investment horizons could therefore diversify into the above markets to reduce portfolio risk by adopting lower frequency trading strategies. The results generally show that stronger co-movements occurring at medium frequencies exist at shorter periods. This appears useful for investors with short term investment needs seeking diversification in the short-to-medium term.

Chapter Four examines whether African equity markets decoupled from, and / or converged with regional and global markets from 2003 to 2014, and analyze the implications of that for shocks spillovers. We first examine convergence with the spectral density unit roots within the neoclassical income convergence framework and later model shock spillovers in a step-wise OLS framework. Using a standard factor model representation of the capital asset pricing model (CAPM), that allows for volatility spillovers pre-, during-, and post- the GFC, we examine whether African stock markets were sheltered from the effects of the crisis regionally and globally. The examination of both regional and global spillover effects is necessary because the transmission mechanism of shocks may either be direct channel from the "birth place or first victim" of shocks (usually the global market) or indirect from neighboring countries/markets that are subsequently affected by the crisis-originating countries/markets.

Three major outcomes are key in this chapter. First, our model allows for the capturing of volatility transmissions in tranquil and crisis periods. This sheds light on the argument that financial markets exhibit explosive volatility during crisis that may spillover to other markets (see also, Engle, 2004; Dungey and Gajurel, 2015). Second, apart from distinguishing spillovers emanating from regional blocks or global markets, our models allow for the examination of whether shocks from a region are as a result of some shock interceptions from global markets or due to 'own shock' (i.e. regional shocks only). It is also instructive to note that, we are able to examine separately shocks propagating from developed or emerging stock markets, and shocks from the commodity markets.

We find evidence of non-convergence of African stock markets. The findings further report increased correlation between individual African stock markets and the regional and global markets during the crisis, with the correlation more regionally driven than globally. Further, spillover of shocks during the 2007-2009 global financial crisis occurred mainly from North Africa, Southern Africa, West Africa, and other emerging markets. The Southern African regional market was the most influential in propagating shocks to the African markets; while South Africa and Nigeria are identified as the most receptive markets to regional shock spillovers during the crisis. We further report that regional markets do not only propagate their own shocks but also shocks intercepted from global markets. The results suggest African equity markets potential decoupling from global shocks than regional shocks during the crisis. We cautiously surmise that the evidence of higher regional cross-border spillover effects may reflect the degree of regional integration, real sector linkages, as well as the degree of openness among countries.

Chapter Five examines the price effects of currency risk and developed stock markets in equity investments in Africa, with particular emphasis on dependence, interdependence, and (extreme) downside spillovers. Further, the chapter sheds light on African stock markets potentials to act as viable investment alternatives for international portfolio investors, both in tranquil and turbulent times. Practically, we attempt to find answers to the following questions: Do exchange rate and developed equity markets price risks contain information that may inform the decisions of international equity portfolio investors? Do stock markets have a discernible influence on each other, and on the dynamics of foreign exchange rates, and vice versa? Are there spillover effects from exchange rates and developed equity markets to African stocks during extreme market conditions? Is there evidence of *shift-contagion* in African stock markets? The key argument for the last question is that, considering the low levels of integration, liquidity, and degree of international investors' participation in African stock markets, the 'shift-contagion'[3] theory proposed by Forbes and Rigobon (2002) may not be entirely tenable for Africa. Knowledge of extreme dependencies between stocks and exchange rates, and among stock markets is of significant importance to policy makers and investors seeking to shield a diversified portfolio against adverse effects of extreme market movements.

We answer the questions first, by examining the margins of stock and exchange rate markets return distributions and test for both the degree and type of their dependence at extreme levels. We model bivariate dependence and spillover structure between local stocks on one hand, and each of developed stock prices and exchange rates, on the other hand using time-invariant and dynamic copulas, to analyze both average movements across marginal and lower-tail risk spillovers. Based on the copulas, we then compute the extreme conditional value-at-risk (CoVaR) in the markets (stocks and exchange rates) to assess downside spillover effects across them. By so doing, we uncovered how large downside price movement for one market affects the stability of the other, conditional on the fact that the other market is under financial distress, as captured by its value-at-risk (VaR). Prior to that, we estimate a univariate GARCH model with leptokurtic innovations to account for asymmetry and fat-tails. Thus, while the fitted GARCH-type model helps to filter returns of both the stock markets and exchange rates and draws their marginal distributions, the extreme value copulas help to model their bivariate dependence structure and spillover effects. The copulas, unlike conventional linear regression models are able to model both the tail dependence and asymmetric tail dependence. We carry out the test for spillover effects by analyzing the significant differences between conditional and unconditional value-at-risk values using the Kolmogorov-Smirnoff (KS) bootstrap technique (Abadie, 2002). Second, we examine the causality between exchange rate and stock markets, and among stock markets for evidences of markets interdependences using the Toda-Yamamoto causality test. Understanding how markets are interrelated could help policy makers and national governments to device strategies on best means to enhance the performance of one, contingent on the other.

We find evidence of non-homogenous weak negative dependence between stocks and the USD and euro (EUR) exchange rates. Except for Egypt, we record evidence of positive significant

[3] The 'shift-contagion' theory talks about increases in cross-market correlations during crisis – see sub-sequent sub-sections for details.

dependencies between all African markets and their developed counterparts. Though, no spillover effects are found for the full-sample period, disaggregating the data into sub-samples show contrasting results. It is observed that propagation of shocks from the GFC had a second round effect in African stock markets. Thus, the impact of the GFC to African economies was not through the credit crunches and liquidity freezes in Phase I of the crisis, but rather through the global recession that followed into the second phase. The findings are consistent with the view that global shocks propagation to developing markets may stagger during crisis and intensify post-crisis. A practical implication from the results is that given the relatively scarce resources and levels of technological know-how available to African governments, efforts to wean the continent's equity markets from adverse effects of global market crashes should be geared towards plans and programmes to mitigate the shocks not at the early stages but latter stages, where the effects to Africa could be prominently felt.

References

Abadie, A., (2002). Bootstrap tests for distributional treatment effects in instrumental variables models. *Journal of American Statistical Association*, 97: 284–292.

African Development Bank (2013). Situational analysis of the reliability of economic statistics in Africa: Special focus on GDP measurement. *African Development Bank, Tunis.*

Alagidede, P., (2008). African stock market integration: Implications for portfolio diversification and international risk sharing. *Proceedings of the African Economic Conference* 2008, p. 26 – 54.

Berkiros, S.D., (2014). Contagion, decoupling and the spillover effects of the US financial crisis: evidence from the BRIC markets. *International Review of Financial Analysis*, 33: 59-69; DOI: dx.doi.org/10.1016/j.irfa.2013.07.007.

Claessens, S., Giovanni, D.A., Igan, D., Luc, L., (2010). Lessons and policy implications from the global financial crisis. *IMF Working Paper* WP/10/14, February, 2010.

Dungey, M., Gajurel, D., (2015). Contagion and banking crisis – international evidence for 2007-2009. *Journal of Banking and Finance*, 60: 271-283.

Engle, R., (2004). Risk and volatility: econometric models and financial practice. *American Economic Review,* 94(3):405-420.

Forbes, K.J., Rigobon, R., (2002). No contagion, only interdependence: Measuring stock market co-movements. *The Journal of Finance*, LVII: 2223 – 2261.

Garham, M., Nikkinen, J., (2011). Co-movement of the Finish and international stock markets: A wavelet analysis. *European Journal of Finance*, 17:409-425.

Ntim, C.G., (2012). Why African stock markets should formally harmonize and integrate their operations. *African Review of Economics and Finance*, 4 (1): 53-72.

Zeileis, A., Kleiber, C., Kramer, W., Hornik, K., (2003). Testing and dating of structural changes in practice. *Computational Statistics and Data Analysis*, 44: 109-123.

CHAPTER TWO

African Stock Markets: A Hub for International Portfolio Diversification?

2. Introduction

At the center of Africa's development agenda is the quest to attract high private capital flows (PCFs).[4] However, although early days of the 21st century saw increases in private capital flows into Sub-Saharan Africa (SSA), advent of the 2007-2009 global financial crisis (GFC) registered some declines due to increased investor risk-aversion, tighter global credit conditions, and developments in the bond markets (Simatele, 2014). The post-crisis declines may also be attributable to international investors' failure to see investments in Africa as viable alternatives.[5] Global shocks contagion is postulated to draw cross-market asset correlations to unity, eroding possible diversification opportunities during market turbulence. At the same time, financial market integration has the possible effect of surging cross-border listings of stocks and amplifying the transmission of shocks with consequences for domestic and the global economy. Thus, the ability of emerging markets' stocks to insulate themselves from effects of global shocks spillovers, in order to offer hedging and diversification opportunities may be anchored on their level of integration and correlation with the origin of the shocks.

The uncertainty about earning higher expected pay-offs in Africa has been a major contributing factor to why Africa appears not to be receiving large portfolio investment flows. Meanwhile, recent crashes in the global economy are offering investors with fresh means to diversify their investments portfolios across diverse geographical regions. The ability of Africa to identify and benefit from such possible international cross-border portfolio investment flows and diversification opportunities requires an understanding of the nature and extent of correlations between its financial markets and the global economy. For this reason, to ascertain whether equities in Africa can act as sure hubs for international portfolio investors, we ask the questions: are African stock markets in a position to attract large portfolio investments flows during extreme global equity and commodity markets conditions? Further, how can African stocks be deemed viable to offer hedge or act as diversifiers during varying periods of global equity and commodity markets crashes, uncertainty and volatility?

[4] Our definition of private capital flows includes foreign direct investments (FDIs), portfolio capital flows and debt flows.

[5] Although there appears to be some recovery from Africa's bond and equity markets post-crisis, the gains still remain a minuscule proportion of the overall global equity and bond markets (see also AfDB, 2013; Simatele, 2014).

Answers for the above questions remain virtually non-existent for most developing markets including those in Africa.

The focus on African markets as promising candidates for shielding investors from global commodity and equity shocks is as a result of their potential decoupling from global shock contagion and other markets. As Chevallier and Ielpo (2014) suggests, developed equities have the tendency to co-jump with commodities making them unsuitable for hedging commodity price shocks. Again, African economies remain major global producers and consumers of commodities.[6] Price changes in the commodities markets could therefore reflect the choices and selection of alternative asset classes by both local and international investors.

There is no denying the fact that most sub-Saharan African countries suffer some research vacuum and the literature appears not to pay much attention to these countries despite their centrality in the development of the world economy. It is the objective of this chapter to provide answers to the above questions by examining how African stock markets co-move and correlate with global commodities and financial markets around the 2007-2009 global financial crisis. The GFC is the recent biggest economic meltdown that sparked hikes and downturns in almost all sectors of the global economy (such as stock markets, commodity prices, financial institutions, the industrial sector) leading to high economic and financial uncertainties. For instance, during this period, gold and crude oil prices[7] saw remarkable surges whereas other assets (such as stock prices) realized sharp declines. Considering the increase in the prices of gold and oil following the crisis and the most recent plummets in the prices of gold (example April 2013) and oil (example in June 2014), understanding the connectedness between these global factors and emerging markets' stock returns has become highly relevant. Additionally, owing to the increasing global economic and financial uncertainty, diversifying an asset class via hedging has become very important.

---

[6] Among other things, most African countries are major producers of global commodities. For instance, Cote d'Ivoire, Ghana, Nigeria, and Cameroon are among the top 5 world produces of Cocoa, with Cote d'Ivoire being the leader; South Africa is among the first five gold producers in the world; four African countries (namely, Algeria, Angola, Libya, and Nigeria) are part of the twelve-member OPEC group.

[7] The puzzling commodity price increases in early 2008 can be attributed to informational frictions (Cheng and Xiong, 2013). Both Hamilton (2009) and Kilian (2009) observe that huge commodity demands in China and other emerging economies together with near static commodity decline are responsible for the commodity price booms, excluding the price surges in the first half of 2008 (Cheng and Xiong, 2013) when crude oil prices shot up from over 40% to US$147 per barrel in July, 2008.

Traditionally, empiricists (for example, Baur and Lucey, 2010) have defined a hedge (diversifier) as an asset that is uncorrelated (negatively correlated) with another asset or portfolio on average (in crisis periods). Baur and Lucey (2010) further distinguish between a hedge, a diversifier, and a safe haven property of assets as follows: an asset or portfolio is considered as a hedge if on average it is seen to be uncorrelated or exhibit negative correlation with another asset or portfolio. A diversifier is that asset or portfolio which is positively (but not perfectly correlated) with another asset or portfolio on average. Finally, an asset is regarded as a safe haven if it is uncorrelated or negatively correlated with another asset in turbulent periods of the market (see also Hood and Malik, 2013). In furtherance to the above and more precisely, Baur and McDermott (2010) distinguished that a strong (weak) hedge and safe haven is an asset that is, on average, negatively correlated or uncorrelated with another and only in times of market turbulence. Despite the aptness of the above definitions and classifications, the chapter argues that the hedge, safe haven, and diversifier hypothesis proposed above may not hold at all times. The applicability of these definitions may depend on what asset classes are being considered. In contrast to the view held by Baur and McDermott (2010) that increasing correlation between asset classes (in this case commodities and stocks) erode possible diversification opportunities, Oslon *et al.,* (2014) propose that provided the correlation coefficient rises in absolute terms, increased correlations would mean that commodities/stocks can offer better diversification or hedging avenues. This is based on the premise that since hedging entails taking a long position in one asset (as in stocks) and a short position in another (say a commodity), a surge in correlations means that a fall in the commodities futures/spot market would be better offset by a long position in the stock markets, thereby making the hedge effective. Earlier studies by Baur and Lucey (2010) and Baur and McDermott (2010) tested the hedge and safe haven hypothesis on gold and stock or bond returns, with the view that gold or bond returns may offer better diversification opportunities during extreme shocks in the stock markets. In contrast, this chapter is of the view that Africa's less integrated nature with the rest of the globe enhances its capabilities to offer better hedging and diversification characteristics when global markets fall.

2.1 Overview of stock markets development in Africa

This section provides overview of the generality of development characteristics of stock markets in Africa. Detailed description of the development characteristics of most individual stock markets in Africa can be found in Alagidede (2008) and Kodongo and Ojah (2011).

As can be seen from Table 2.0, with about 27 properly functioning exchanges (ASEA, 2013), total number of listed companies in Sub-Saharan African (SSA) equity markets increased from 911 in 2005 to 932 in 2011, though highly incomparable to corresponding figures from South Asia, East Asia and Pacific. With the exception of South Africa, liquidity levels of African stock exchanges are very low, exerting significant setbacks on the growth of markets. Between 2005 to 2011, total market capitalization of SSA stocks increased from US$605,113 to US$951,930, with South Africa alone accounting for 93.4% (2005) and 90.0% (2011). Growth in turn-over ratios (values of traded shares as a percentage of market capitalization) in SSA appeared stalled between 2005 to 2011, decreasing marginally from 37.3% to 37.2%.

Generally, stock markets in Africa can be categorized into four, similar to the classifications by Smith *et al.,* (2002) and later observed by Ntim (2012):

i. South Africa – the largest and the oldest stock market in SSA.
ii. A group of medium-sized markets, consisting of Egypt, Kenya, Nigeria, Morocco, Tunisia, and Zimbabwe.
iii. A group of small, but rapidly growing markets, consisting of Botswana, Cote d'Ivoire, Ghana, Namibia, and Mauritius.
iv. A group of very small markets consisting of Libya, Malawi, Mozambique, Sudan, Swaziland, Tanzania, Uganda, and Zambia which are struggling to take off.

In Table 2.1, we analyze the development characteristics of 21 African equity markets as at end of 2014. It is observed that the primary activities on most African stock markets are the issuance of bonds and equities with predominantly online and intraday trading mechanisms. The exceptional market is the South African Johannesburg Stock Exchange (JSE) that issues bonds, equities, and derivatives with online, margin, and intraday trading mechanisms.[8]

Despite the continent's tremendous efforts towards global commodity production, the markets for commodities in national stock exchanges are virtually non-existing. From Table 2.1, it is noticed that most African stock markets have electronic trading systems, trade for averagely 5 hours, and have a three-day settlement period. These developments are however, new and may not be seen to have

[8] It is worth noting that the Egyptian Stock Market also has intraday, online, and margin trading mechanism.

impacted the performances of individual markets (UNDP, 2003; Moin, 2007). As Ntim *et al.,* (2011) observe, as at 2005, only the markets in Egypt, Nigeria, and South Africa had electronic trading systems.

Table 2.0: Indicators of capital market development in SSA and the rest of the world

	Market Capitalization				Market Liquidity		Turnover Ratio		Listed Companies	
	US$ million		% of GDP		Value of shares traded (% of GDP)					
	2005	2011	2005	2010	2005	2010	2005	2011	2005	2011
Sub-Saharan Africa	605,113	951,930	128.6	149.5	43.3	46.6	37.3	37.2	911	932
South Africa	565,408	856,711	228.9	278.4	81.2	93.5	39.3	39.8	388	355
Nigeria	19,356	39,270	17.2	26.3	1.7	2.7	11.5	9.2	214	196
Kenya	6,384	10,203	34.1	46.0	2.7	3.5	9.8	7.1	47	58
Botswana	2,437	4,107	23.8	27.4	0.4	0.9	1.8	3.6	18	23
Cote D'ivoire	2,327	6,288	14.2	31.2	0.2	0.6	1.4	1.8	39	33
Ghana	*1,661*	*3,097*	*15.5*	*11.3*	*0.6*	*0.3*	*3.2*	*4.1*	*30*	*36*
Zambia	989	4,009	13.8	17.4	0.2	1.6	2.0	-	15	20
Tanzania	588	1,539	4.2	5.5	0.1	0.1	2.3	2.5	6	17
East Asia & Pacific	1,212,704	4,638,422	40.1	79.9	25.6	113.3	68.4	154.3	3,931	5,181
Europe & Central Asia	789,576	1,116,849	48.7	51.8	22.7	42.7	61.6	121.1	6,564	4,368
Latin America & Carribean	1,028,157	2,274,194	40.5	57.6	9.9	22.9	28.4	46.4	1,504	1,446
Middle East & North Africa	135,018	265,561	36.8	34.6	7.2	7.5	39.3	19.4	1,531	1,012
South Asia	609,110	1,095,645	58.8	81.9	55.7	52.6	111.6	55.4	6,050	6,400
Euro Area	6,357,326	5,482,967	62.7	51.7	73.1	47.1	120.5	110.4	6,737	6,250

Source: World Development Indicators (2013).

Despite the major setbacks, one interesting development in the continent's stock markets is the openness to foreign participation, although individual countries have some restrictions to non-resident foreign investors' holdings on local bourses. This high market openness to non-resident foreign investor's opens doors for higher portfolio flows to the stock markets. For instance, between 2010 and 2012 fiscal years, net private capital flows to Sub-Saharan African countries doubled, compared with the 2000-2007 periods. In year 2013, portfolio and cross-border bank flows into SSA markets outstripped the US$17 billion mark in 2012. Dominant beneficiaries were Nigeria, Zambia and Ghana, and an estimated portfolio flows recorded by these countries stood, respectively, around 2.7, 1.6 and 1.9% of gross domestic product (GDP).[9] As high levels of international equity flows are realized, the interdependence between stock returns and exchange

[9] Figures are gleaned from various statistical bulletins of the IMF and World Bank.

rates becomes widespread (Boako *et al.,* 2016). This occurs since increasingly high levels of cross-border equity flows creates a higher demand for and supply of currencies, in which international equity prices are denominated (Kanas, 2000).

It does appear that the struggle to move African stock markets from manual to automation trading systems is yielding significant results. That notwithstanding, structural developments in stock markets in African still lag behind their global and other emerging market counterparts. Currently, African stock markets are organized as mutual entities (Senbet and Otchere, 2008) whilst demutualization is the order of the day. Demutualization breaks the jinx of monopoly, enhances gains from competition, and improves corporate governance. Additionally, demutualization transforms an exchange from a non-profit entity into a profit entity through a change in the legal status and governance structure in the exchange (Senbet and Otchere, 2008). Though data on the status of demutualization on African stock exchanges is not known with exactitude, some countries have initiated the process and it is expected that within the next decade some successes will be chalked.[10]

2.2 Review of related studies - *Commodities and equities: A "market of one"?*

Increased susceptibility of financial markets to various forms of economic shocks has led to the resurgence of investors' appetite to look for alternative means to hedge their downside market related risk. In the last decade, investors have considered commodities as highly liquid financial assets other than a means to support 'real' economic activity through hedging and risk management (Gilbert, 2009; Vivian and Wohar, 2012; Cheng and Xiong, 2013; Yang and Garcia, 2014). A report by the US Commodities Futures Trading Commission (CFTC) in 2008 showed that investment inflows to various commodity futures markets rose to US$200 billion from 2000 to 2008 (CFTC, 2008). This figure had jumped to about US$210 billion by the end of 2012.[11]

[10] For example, the Ghana Stock Exchange (GSE) initiated the process of market demutualization in 2015 though implementation has stalled.
[11] See CFTC Index Investment Data. http:/www.cftc.gov/MarketReports/IndexInvestmentData/index.htm

Table 2.1: Institutional, operational, and infrastructural development characteristics of African stock markets as at end of 2014.

Market	Trading mechanism			Trading hours	Trading system	ASEA status	Foreign investment	Commodities exchange	Clearing and settlement	Demutualization	Primary market activity
	margin	intraday	online								
Botswana	No	Yes	Yes	10^{30}-13^{30}	Automated	Yes	Yes	No	T + 3	No	Bond & equity
Cote D'Ivoire	No	Yes	No	8^{30}-10^{30}	Electronic	Yes	Yes	No	T + 3	No	Bond & equity
Tunisia	No	No	Yes	9^{00}-14^{10}	Electronic	Yes	Yes	No	T + 3	-	Bond, cash & equity
Casablanca	No	Yes	Yes	9^{00}-15^{40}	Electronic	Yes	Yes	No	T + 3	-	Bond & equity
Tanzania	No	No	Yes	10^{00}-14^{00}	Automated	Yes	Yes	No	T+3	-	Bond & equity
Cameroon				9^{00}-11^{00}		Yes	Yes	No	T+3	-	Bond & equity
Egypt	Yes	Yes	Yes	9^{45}-14^{30}	Electronic	Yes	Yes	No	T+3	-	Bond, cash & equity
Ghana	Yes	No	Yes	9^{30}-15^{30}	Automated	Yes	Yes	No	T+3	-	Bond & equity
South Africa	Yes	Yes	Yes	9^{00}-17^{00}	Electronic	Yes	Yes	Yes	T+5	Yes	Derivatives, interest rate & equity
Rwanda	No	Yes	No	9^{00}-12^{00}	Electronic	Yes	Yes	No	T+2	-	Bond & equity
Zambia				11^{00}-14^{00}	Automated	Yes	Yes	Yes	T+3		Bond & equity
Malawi	Yes	Yes	Yes	10^{30}-13^{30}	Manual	Yes	Yes	No	T+5	No	Equity
Mauritius	No	Yes	Yes	9^{00}-13^{30}	Electronic	Yes	Yes	No	T+3	-	Bond & equity
Mozambique	No	Yes	Yes	8^{00}-16^{00}	Electronic	Yes	Yes	No	T+3	-	Bond & equity
Kenya	No	Yes	No	9^{00}-15^{00}	Electronic	Yes	Yes		T+3	-	Bond & equity
Namibia	Yes	Yes	No	9^{00}-17^{10}	Electronic	Yes	Yes	No	T+5	-	Bond & equity
Nigeria	Yes	Yes	Yes	9^{30}-14^{30}	Electronic	Yes	Yes	No	T+3	-	Bond & equity
Uganda	No	No	No	10^{00}-12^{00}	Manual	Yes	No	No	T+5	-	Bond, cash & equity
Zimbabwe	No	Yes	No	10^{00}-11^{00}	Automated	Yes	Yes	No	T+7	-	Equity
Sudan	No	Yes	No	10^{00}-11^{00}	Electronic	Yes	Yes	No	T+5	-	Equity
Cape Verde	No	Yes	No	8^{30}-15^{00}	Automated	Yes	No	No	T+0	-	Bond & equity

Source: African Securities Exchanges Association (ASEA), World Federation of Exchanges (WFE), and websites of all exchanges.

At the same time significant number of commodities across the energy, metal, and agricultural sectors saw a synchronized boom and bust cycles just around the GFC in 2007-2008 (Cheng and Xiong, 2013). This huge inflow is necessitated by the believe that investors potential to diversify can better be enhanced with the inclusion of commodity futures since commodities show equity-like returns and low correlation with traditional assets (Gorton and Rouwen-horst, 2006). The process of speculative market participants' consideration of commodities as investment assets is referred to as the "financialization" of commodities.[12] Including commodities in investors' portfolios therefore appears to be a glowing venture generating higher interest. Commodities, just like all assets (such as stocks and bonds) show sensitivity to changing economic conditions and tend to correlate with asset returns, regardless of what explains such correlations. Establishing evidence to explain how increased investor appetite for commodities reflects the pricing of financial securities and facilitate the commodity-equity cross linkages have always attracted the attention of analyst and scholars.

Evidence abounds to suggest that "financialization" of commodities partly explains the increases in cross-market correlations between commodities and equities during crisis (Olson *et al.,* 2014; Buyuksahin and Robe, 2014)[13], even though the existence of commodity financialization is in serious doubt (see for example, Demirer *et al.,* 2015)[14]. The commodity-equity correlations may also be driven by herd behavior (Demirer *et al.,* 2015). In case a price change in commodities is driven by commodity financialization, it can be argued that equity market shocks may lead to herding in the commodity market. The herding behavior could usher asset prices not to show substantial deviation from the overall market (Chang *et al.,* 2000). Thus, as market participants subdue their own beliefs and make investment choices that are driven by market sentiments the correlated behaviour of traders may cause portfolio returns to show higher co-movements, resulting in lower deviations within the commodity portfolio (Demirer *et al.,* 2015).

[12] See also Cheng and Xiong (2013) and Olson *et al.,* (2014). Additionally, Tang and Xiong (2012) define commodity financialization as the increasing influence of the financial sector relative to the real sector over market prices and returns dynamics in commodity markets.

[13] It is also plausible to think that other factors other than financialization may drive the correlation between equities and commodities. For instance, the spike in correlations between energy and stock market prices in 2008-2009 may have occurred due to worsening global economic conditions.

[14] Applying a regime-switching model to examine the role of the stock market in driving herd behaviour in commodity futures market, the authors conclusively denounce the existence of the financialization hypothesis. Again, Krugman (2008), Hamilton (2009), and Kilian (2009) fail to embrace the hypothesis and contend that commodity prices cycles are market driven (under the forces of demand and supply in global markets), largely fueled by growth patterns in emerging economies.

Theoretical justification for the commodity financialization hypothesis can be put under three strands. The first strand observes that because commodities are generally segmented from other financial markets (Bessembinder, 1992) and less constrained than others (Teo, 2009) financialization strengthens cross-market linkages if the increases in financialization reflect new entrants or traders not previously in these markets (Buyuksahin and Robe, 2014). Second, financialization can lead to cross-market shock contagion (Kyle and Xiong, 2001; Broner *et al.,* 2006; Buyuksahin and Robe, 2014) and risk-sharing (Cheng and Xiong, 2013) between commodities and equities. The 'hedging pressure' theory suggests that hedges are typically on the short side of futures markets requiring them to offer positive risk premia to attract speculators to take long positions (Keynes, 1923). Tang and Xiong (2012) posit that financialization improves risk-sharing by moderating the hedging pressure when a large pool of financial investors takes a long position. However, financial investors also have time-varying risk appetites owing to risk constraints and financial distress (Cheng *et al.,* 2012). For instance, when investors who have already taken long positions suddenly realize that price reductions in other assets may offer them opportunities to mitigate losses, they would obviously wind-up on their long position. This can effectively lead to the transmission of exogenous shocks to commodity markets.[15]

To this end, "financialization" can be seen as affecting risk sharing in commodities through the double role of financial investors: as providers of liquidity to hedges when trading to accommodate hedging needs and as consumers of liquidity from hedges when trading for their own needs" (Cheng and Xiong, 2013; pp. 2). Thirdly, financialization may also affect informational discovery in commodity markets. Heterogeneous expectations among financial investors under informational asymmetry can lead to drift in commodity futures prices (Singleton, 2012). According to Sockin and Xiong (2012) trading noise of financial investors in futures markets can lead to feed-back effect to the commodity demand of final goods. It thus makes it difficult for producers of goods to decipher whether changes in futures prices occur based on investor trading or developments in global economic environments. This reduces opportunities for arbitrage profits and consequently results in the decoupling of markets that had earlier been linked up.

Empirical evidence on the impact of financialization produces interesting results albeit differences. Earlier studies by Bodie and Rosansky (1980) and Ankrim and Hensel (1993) give evidence that

[15] Cheng and Xiong (2013)

adding commodities to portfolios enhances investors' chances of reducing risk. However, recently, Daskalaki and Skiadopoulos (2011); You and Daigler (2013) do not show diversification benefits in out-of-sample setting; but Jahan-Parvar *et al.,* (2012) provide evidence in support of in-sample predictability from commodities to equities. In their application of the mean-variance optimization framework to examine the significance of commodities in investors' portfolios, Yang and Garcia (2014) report that even though commodities can slightly reduce risk in portfolios, this effect becomes negligible in well balanced portfolios. Olson *et al.,* (2014) uses volatility impulse response functions from a multivariate BEKK model to investigate the relationship between energy and equity markets and find that low S&P 500 returns cause substantial increase in the volatility of the energy index.

The part of the literature examining the interconnectivity between commodities and equity markets produce varying results. Whereas Buyuksahin and Robe (2014) establish that the correlation between returns on commodity and equity indices increases with the participation of speculators in hedge funds that hold positions in both equity and commodity futures markets in particular (see also Sivennoinen and Thorp, 2013), Buyuksahin *et al.,* (2008) find no evidence of time-varying co-movement between equity and commodity index returns for the 1991-2007 period. The author's conclusion was that commodities can be highly considered as a viable diversification tool for portfolio investors. Most of these studies have largely focused on developed and emerging markets in Europe, Asia, and North American leaving a substantial vacuum in the African context.

Theoretically, the equity pricing model suggests that oil price changes can impact stock prices through two channels: the expected discount rate and expected cash flow. Since oil price constitutes significant portion of a firm's input costs, a company's marginal costs of production can be driven by higher oil prices. Again, higher oil price volatilities may raise uncertainties about the prospects of future energy market conditions which can affect investment behaviour leading to declines in investments (Xu, 2015). Since the price of a stock is a function of the discounted present worth of expected future cash flows, as investors begin to cut investments in stocks the reduced cash flow can adversely affect stock prices. The reverse is true if rising oil prices causes investors to increase their investments in stocks.[16] On account of the US Energy Information Administration (EIA) estimates

[16] This may be depending on whether the firm produces or consumes oil. Park and Ratti (2008) contend that an increase in the price of oil is not always a bad news for the equity market. "Shocks emanating from oil prices may be bad news

based on the OECD model that an increase in the barrel price of crude oil by US$25 to US$35 causes a two-year drop in the gross domestic product (GDP) of 0.3, 0.4, and 0.5 percentage points in the US, Japan, and Eurozone respectively, we argue that if crude oil price constitute such a decisive factor in economic growth then upturns in world market crude oil prices will meaningfully enhance firms' future cash flows and ultimately their equity prices. In anticipation of higher inflation resulting from increasing oil prices monetary policy makers may increase interest rates (Bernanke 1983; and Pindyck, 1991). The corollary effect of this can be a decrease in stock prices through the discount rate channel. This is true since the discounted dividend model (DDM) posits that equity prices are inversely related to interest rates (and a rise of interest rates imply higher required rate of return).

Empirical literature examining the oil-stock nexus can be put under two main categories depending on the level of aggregation (Xu, 2015): aggregate level (e.g. Huang and Guo, 2008; Frimpong, 2009; Adu *et al.,* 2013; Boako *et al.,* 2015) and disaggregate level (e.g. Lee and Ni, 2002; Arouri and Nguyen, 2010; Nayaran and Sharma, 2011; Xu, 2015). There are different strands of this literature but four are discussed in this chapter. The first strand examines the effects of crude oil prices on equity prices and provides conflicting results. Park and Ratti (2008) finds significant positive effect of oil price increases on stock returns in Norway (as an oil exporter). Similarly, Phan *et al.,* (2015) report that equity returns of countries that produce oil respond positively to oil price changes regardless of whether oil prices experience upswings or downturns. Aloui and Jammazi (2009) apply a Markov-switching regime model to examine the relationship between stock returns and crude oil prices and find that rising oil prices have significant roles in the determination of both the volatility of stock returns and probability of transition across regimes.

While some studies show negative relationship between crude oil price and stock prices (see for example, Wei, 2003) others give mixed results. For example, while Huang and Guo (2008) show evidence of negative oil price effect on stock prices, Nayaran and Sharma (2011) reveal that oil-related sectorial returns react positively to oil price changes whilst other sectors (consumer, financial

for the stock market only when high oil prices arise from oil market-specific demand shocks related to shifts in the precautionary demand for crude oil in response to concerns about shortfall in future production" (Xu, 2015, pp. 2610), services, etc.) returns react positively.[17] The second strand of literature examines whether oil price shocks exert asymmetric (e.g. Arouri, 2011) and or non-linear (e.g. Rafailidis and Katrakilidis, 2014) effects on aggregate equity market returns. Phan *et al.,* (2015) – at the disaggregated level and Odusami (2009) – at the aggregate level for example, use the asymmetric GARCH model on stock-oil nexus and report asymmetric and non-linear effects of crude oil prices on stock returns respectively. The gradual diffusion hypothesis (GDH) proposed by Hong and Stein (1999) and later popularized by Hong *et al.,* (2007) forms the basis of the third strand of the literature. The GDH which generally intuits that the effect of oil price shocks to stock prices is not instantaneous but builds over time tests the lagged effect of crude oil prices on stock returns (e.g. Jones and Kaul, 1996; Driespong *et al.,* 2008). For example, Vo (2011) uses a multivariate volatility structure on the relationship between oil and stock market volatility and finds that the correlation between the two markets follows a time-varying dynamic process and tends to increase when the markets are more volatile. The author further reveals that past volatility of the stock (oil futures) markets show predictive power over the future volatility over oil futures (stock) market. Xu (2015) also reports that in an out-of-sample framework, lagged oil price variations predict industry equity returns in UK. The fourth strand of the literature focuses on the predictive power of oil prices on equity returns. Gupta and Modise (2013) examined both in-sample and out-of-sample predictive power of macroeconomic variables on South African stock returns using monthly data from 1990 to 1996 (for in-sample period) and from 1997 to 2010 (for out-of-sample period) and find that for the in-sample period, world growth in oil production exerts some predictive power on stock returns for short-horizons. At the aggregate level, Xu (2015) establish proof of the predictive power of fluctuations in oil prices on industry asset classes in UK.

Owing to the growing uncertainty of financial markets growth in recent times financial investors have sought diverse avenues to diversify market related risks through hedging. This has made investments in gold very appealing in current times, especially during market crashes. Gold as a financial instrument has the attributes of commodity, currency, and serves as a store of value. The potential of gold to mitigate risk has been well documented in earlier literature that examined the dollar- or stock-hedge (see Tully and Lucey, 2007; Arouri *et al.,* 2015; Zagaglia and Marzo, 2013),

[17] This happens because each industry is heterogeneous based on the differences in their market structures, competition and concentration levels, and whether oil acts as a key input or output of the industry. Therefore their stocks prices' responses to changes in oil prices may differ on the basis of the industry nature and shock transferring abilities.

inflation-hedge (e.g. Worthington and Pahlavani, 2007; Blose, 2010; Beckmann and Czudaj, 2013), portfolio diversification (e.g. Hillier *et al.,* 2006), as well as safe-haven (e.g. Baur and McDermott, 2010; Ciner *et al.,* 2013) characteristics of gold. Conventional finance theory suggests that for gold to act as a dollar or stock hedge, its price should be negatively related to the strength (price) of the dollar or stock. Again, the inflation hedge feature of gold is seen if gold's price is seen to be correlated with the price index of a basket of goods (Bialkowski *et al.,* 2014). Finally, gold becomes a portfolio diversifier or safe haven for asset classes such as stocks or bonds if the price of gold is uncorrelated or negatively correlated with the asset returns (during market crisis).[18] Even though financial market contagion is noted to drive correlations between different classes to unity in times of crisis, gold is still believed to be uncorrelated with other assets (Baur and Lucey, 2010) and a zero-beta asset (McCown and Zimmerman, 2006).

Empirical literature investigating the relationship between gold and stock returns are basically segmented into two: investment portfolio diversification, safe haven, and hedging opportunities; and the nature of influences of gold on stock markets. Beckmann *et al.,* (2014) apply an exponential transition function to examine the hedge (safe haven) property of gold for stocks for 18 individual markets and five regional indices from 1970 to 2012. The study that look at two extreme regions – one accounting for periods in which stock returns are on average (which allows to check whether gold is a hedge for stocks) and the one that accounts for periods characterized by extreme market conditions with high volatility for stocks (which allows to test safe haven property of gold), finds evidence in support of both the hedge and safe haven characteristics of gold for stocks. Baur and McDermott (2010) reports that gold acts as a hedge and a strong safe haven for European countries as well as US, however it fails to act as a hedge or safe haven for emerging economies of Canada, Australia and Japan. Other studies (e.g. Pasutasarayut and Chintrakarn, 2012) fail to establish either safe haven or hedge ability of gold for stocks. Some studies also examine the nature and extent of volatility spillover between gold prices and stock returns. For example Arouri *et al.,* (2015) apply various multivariate GARCH models in related studies for China from 2004 to 2011 and report that there is significant volatility cross effects between prices of gold and Chinese stock prices. The

[18] See also Baur and Lucey (2010) and Bialkowski *et al.,* (2014). Baur and McDermott (2010) strongly distinguish between strong (weak) hedge and safe haven as when on average one asset is negatively correlated (uncorrelated) with another, respectively in periods of market crisis.

authors further suggest that factoring gold into investment portfolios in China enhances the returns (on risk-adjusted basis) and helps to effectively hedge against equity risk exposure.

In spite of the recent renewed interest among finance scholars, practioners and investment analyst on the dynamic interactions between changes in commodity prices and stock returns, most of the related studies have largely focused on developed economies and emerging markets in Europe, Asia, and North America. To this end, extant literature (which are mainly producing conflicting results) have either not specifically considered the periods of the 2007-2009 global financial crisis or included more commodities in their frameworks. There is therefore a huge vacuum in the literature on Africa. However, considering the fact that Africa was largely touted to have decoupled from the global economic environment during the crisis, there could be huge portfolio diversification opportunities for international investors seeking to diversify or hedge risk across different asset classes.

In Africa, a quick scan through the literature exploring the stock-commodities nexus reveals Frimpong (2009), Adu *et al.,* (2013), Mensi *et al.,* (2014), and a few others. Of the above studies, only Mensi *et al.,* (2014) considers a broad spectrum of different financial markets across the continent (including, Egypt and South Africa) and delves into the dependence structure between commodities and equities without exploring the opportunities for hedging and diversification. Again, the studies reviewed mainly focus on the roles the commodities played in providing hedges and diversification properties for equities and not the other way round. This chapter contributes to the literature by helping address the paucity of extant literature in the field. Specifically, we include in our models countries which are producers of gold (South Africa and Ghana), oil (Nigeria), and Cocoa (Coite d'Ivoire and Ghana), whist factoring the tranquil and crisis periods of the GFC, and also examining the hedging and diversification features of stocks different from previous studies.

2.3 Data and research design

2.3.1 Data

Data for the study comprise indices of eleven (11) African stock markets. First, these markets represent the largest stock markets in Africa, accounting for the bulk of continental total market capitalization. They could therefore proxy for stock markets in the rest of the continent. Their inclusion in the sample is based on market size, trading volume, and sub-regional representation.

Second, all eleven (11) markets sampled are open to international portfolio investment despite disparities in the level of openness. We also include in the sample spot prices of five (5) global commodities (gold, oil, silver, platinum, and cocoa)[19] and an aggregate commodity price index (i.e. the Bloomberg Commodities Index – BCOM)[20], as well as, two global equity indices - the Standard and Poor 500 (S&P 500) index and the Morgan Stanley Capital International World index (MSCI-W), which includes developed and emerging markets. The included commodities have significance in international trade and African economic development, as most of them are produced on commercial scale in the continent. The data are gleaned from Bloomberg on a daily close-to-close basis from 3 January 2003 to 29 December 2014 (a total of 3,056 observations); and expressed in a common currency (using the US dollars (US$)) to ease comparison; a practice that has become ubiquitous in empirical studies of international financial markets – Pukthuanthong and Roll (2009).

We therefore assume that hedging and/or diversification opportunities are viewed from the perspective of international investors. The use of the close-to-close (see also Brooks and Persand, 2001) method is to mitigate any problems arising from non-synchronous trading (since trading days for the different markets differ in the week). The method is executed by eliminating observations for all markets if the price index for a given market is not available for a given date. Thus, we limit our sample to only days for which we have observations for all markets. Empirical analyses are conducted with continuously compounded returns computed as:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) * 100 \qquad [2.0]$$

where r_t = returns at time t; p_t and p_{t-1} are respectively current price/index and one-period lagged price/index.

In order to capture the effects of the GFC in our models, two methods are adopted. One is the use of a dummy, and the other is data disaggregation. The latter puts the data into full sample and sub-

[19] Alternatively, we could have relied on futures prices. However, as indicated by Vivian and Wohar (2012), spot prices constitute the underlying securities upon which derivatives are based. Relying on spot prices is also noted to avoid issues related to rollover of futures contracts (Creti *et al.,* 2013).

[20] The index with a base value of 100 as of 31 December, 1990 and computed every 15 seconds is made up of 22 exchange-traded futures on physical commodities. The represented commodities are weighted to account for economic significance and market liquidity. Commodity weights are based on production and liquidity subject to weighting restrictions applied annually such that no related group of commodities constitute more than 33% of the index and no single commodity constitutes more than 15%.

sample (global financial crisis) periods. Akin to Lean and Nguyen (2014), the global financial crisis (GFC) is considered to have commenced on 15 September 2008 and eased on 30th May, 2009. Our disaggregated data then comprise (a) full sample period from 3rd January, 2003 to 29th December, 2014; and (b) a sub-sample (crisis) period covering 16th September 2008 to 1st June, 2009.

2.3.2 The extended market model

To examine risk-return trade-off of portfolio investments in the African markets, we specify an extension of the capital asset pricing model (CAPM) – see also Anghelache (2012) and Keith and Nitzche (2005). The estimation of the CAPM model in this study is done for the full sample period. However, in order to capture the effects of the GFC, a dummy variable (D_t) taking the value one (1), during the GFC period and zero (0) otherwise is chosen. We estimate this model to determine the global index that exerts the highest influence on Africa's unexpected average excess returns on risk-adjusted basis in the full-sample and GFC period. The extended excess return market model (static approach) is specified with D_t as:

$$(r_{it} - r_f) = \beta_0 + \beta_1(r_{mit} - r_f) + \beta_2 D_t + \varepsilon_t \qquad [2.1]$$

where r_{it} = returns on African stocks; r_{mit} = returns on global indices (BCOM, S&P 500, and MSCI-W), which serve as benchmark market portfolios; ε_t is the error; r_f = risk-free interest rate (in this case, considered as the U.S 1-month Treasury bill rate)[21] since returns are measured in US$.

To be able to capture the impact of the global commodities (GC) on the African stocks, the following augmented market model is specified, similar to Lean and Nguyen (2014).

$$(r_{it} - r_f) = \alpha_0 + \beta^{*}{}_0(r_{mit} - r_f) + \sum_{j=1}^{n} \alpha_j \Delta \ln(GC)_{jt} + D_t\left[\delta_0 + \beta_1^{*}(r_{mit} - r_f) + \sum_{j=1}^{n} \delta_j \Delta \ln(GC)_{jt}\right] + \varepsilon_t \qquad [2.2]$$

where $\beta^{*}{}_0$ and $\beta^{*}{}_1$ are measures of market-wide risk in the full sample and GFC periods respectively; n is the total number of commodities (which is 5); $\alpha_j\,(j = 1, 2, ..., 5)$ and $\delta_j\,(j = 1, 2, ..., 5)$ denote the marginal effects of the commodities on equities in Africa for the full sample and GFC periods respectively. All other notations are as previously defined in Equation (2.1).

21 The 1-month Treasury bill rate is sourced from the website of the Federal Reserve Bank of St. Louis https://research.stlouisfed.org/fred2/categories/116

2.3.3 Modeling dynamic conditional correlation (DCC)

We adopt the Engle (2002) DCC model to estimate the time-varying correlation between African stocks and global economic factors (i.e. global commodities and equity indices). Principally, we seek to examine the hedging and diversification opportunities across the eleven African markets. The DCC-GARCH model will also help to estimate the volatility cross-effects and their persistence – a key issue with implications for investors' portfolio selection and allocation decisions. The Engle (2002) DCC model can be estimated in two phases: first by estimating univariate GARCH (1,1) parameters and second estimating the coefficient of the conditional correlations. Thus, the model allows for the separate specification of the conditional variances on one hand, and the conditional correlation matrix on the other hand.

For an m x 1 vector of asset returns, $r_t = \left(r_{it}, ..., r_{mt}\right)'$ with conditional mean and variance, we express the *m* x *m* conditional covariance matrix as:

$$H_{t-1} = D_{t-1} R_{t-1} D_{t-1} \qquad [2.3]$$

$$D_{t-1} = \begin{bmatrix} \sigma_{1,t-1} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t-1} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & 0 & \cdots & \sigma_{m,t-1} \end{bmatrix} \qquad [2.3.1]$$

$$R_{t-1} = \begin{bmatrix} 1 & \rho_{12,t-1} & \rho_{13,t-1} & \cdots & \rho_{1m,t-1} \\ \rho_{21,t-1} & 1 & \rho_{23,t-1} & \cdots & \rho_{2m,t-1} \\ \vdots & & \ddots & & \vdots \\ \vdots & & & & \rho_{m-1,m,t-1} \\ \rho_{m1,t-1} & \cdots & \cdots & \rho_{m,m-1,t-1} & 1 \end{bmatrix} \qquad [2.3.2]$$

where D_{t-1} is an *m x m* diagonal matrix with elements $\sigma_{i,t-1,}\ i = 1, 2, ..., m$ representing the conditional volatilities of asset returns, and R_{t-1} denotes the symmetric *m x m* matrix of conditional correlations. We specify the conditional volatility of the *ith* asset returns as given below:

$$\sigma_{i,t-1}^2 = Var\left(r_{it} \mid \Omega_{t-1}\right) \qquad [2.3.3]$$

in which case Ω_{t-1} is the information available at time *t-1* and *Var* is the variance of the asset returns.

The GARCH (1,1) model of $\sigma^2_{i,t-1}$ is then estimated as:

$$\sigma^2_{i,t-1} = \bar{\sigma}^2_i \left(1 - \lambda_{1i} - \lambda_{2i}\right) + \lambda_{1i}\sigma^2_{i,t-2} + \lambda_{2i} r^2_{i,t-1} \qquad [2.3.4]$$

where $\bar{\sigma}^2_i$ is the unconditional variance of the *ith* asset return *(r)* and $\lambda_{1i}, \lambda_{2i}$ are unknown parameters.

The conditional correlations between assets *i* and *j* can be estimated as:

$$\tilde{\rho}_{ij,t-1}(\phi) = \tilde{\rho}_{ji,t-1}(\phi) = \frac{q_{ij,t-1}}{\sqrt{q_{ii,t-1} q_{jj,t-1}}}, \qquad [2.3.5]$$

for $-1 \leq \rho_{ij,t-1} \leq 1,$ and $\rho_{ij,t-1} = 1,$ for $i = j$

and $q_{ij,t-1} = \tilde{\rho}\left(1 - \phi_1 - \phi_2\right) + \phi_1 q_{ij,t-2} + \phi_2 \tilde{r}_{i,t-1} \tilde{r}_{j,t-1}$

In the above equation, $\bar{\rho}_{ij}$ denotes the unconditional correlation, $\tilde{r}_{i,t-1}$ is standardized asset returns, and $\phi_1 \; and \; \phi_2$ are non-negative scalar parameters with a sum less than unity i.e. $\phi_1 + \phi_2 < 1$.[22]

2.3.4 Econometric approach to the hedging and diversification analysis

This section provides detail insights on the examination of whether African stocks can act as diversifiers and hedges in extreme conditions of the commodity markets. Particularly, we examine whether African stocks can strategically serve as viable investment hubs for international investors during sell-offs or crashes in international commodity markets. We assume that returns on Africa's stocks are dependent on the general price trends in the commodity futures/spot markets. Additionally, we contemplate that the relationship is not constant but driven by some extreme market conditions. In line with Baur and Lucey (2010) and Baur and McDermott (2010) we apply the regression model given by Equations (2.4 – 2.4.2) to test the hedge and diversifier property of African stocks.[23] We in-turn model the behaviour of African stocks (AFSTOCKs) as follows - (*each other variable [EOV] specific co-efficients are suppressed for brevity of exposition*).

[22] Returns are standardized to achieve normality (see also, Pesaran and Pesaran, 2009).
[23] Baur and Lucey (2010) and Baur and McDermott (2010) applied the technique to bonds and gold. However, we are not in anyway, suggesting that equities are like bonds or gold.

$$r_{AFSTOCKt} = a + b_t r_{(EOV),t} + \varepsilon_t \tag{2.4}$$

$$b_t = d_0 + d_1 D\left(r_{EOV} q_{10t}\right) + d_2 D\left(r_{EOV} q_{5t}\right) + d_3 D\left(r_{EOV} q_{1t}\right) \tag{2.4.1}$$

$$h_t = \pi + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2 \tag{2.4.2}$$

Equation (*2.4*) models the relations between African stocks and global commodities. The parameters for estimation are *a* and *b*, with the error term given by ε_t. The parameter b_t is modeled as a dynamic process given by equation (*2.4.1*). In equations (2.4) and (2.4.1), $r_{AFSTOCKt}$ refers to returns on the considered stock markets in Africa (individually); r_{EOVt} indicates returns of the regressors (all commodities) at time *t*. The parameters of interest in Equation (*2.4.1*) are the constant term, d_0 (which measures average effect of the predictor variables on the response variable – and in this case our statistic for determining a hedge property); and dummy variable coefficients $d_1, d_2, and\ d_3$. The dummy variables denoted as *D*(…) capture extreme market behaviour of the regressors and are coded 1 if the commodity returns go beyond a certain threshold given by the 10%, 5%, and 1% quantile (*q*) of the return distribution.[24] The quantiles account for asymmetries of positive and negative (extreme) shocks and are included to focus on declining moments of the commodity markets. For instance, we are interested in finding out whether declining moments in these markets propel international portfolio investors to consider African stocks as safe destinations for their investments. The intuition here is that considering the weak level of integration[25] between African stocks and the global financial environment, there may be the possibility of Africa's decoupling from global shock contagion leading to lower or negative cross-assets correlation between Africa and the international markets.

The structure in Equation (2.4.1) assumes that returns on African stocks are dependent on the contemporaneous return on each other asset (cocoa, gold, oil, silver, platinum, and BCOM). This is consistent with the diversification hypothesis. It is additionally assumed that African equity returns do not drive changes in prices on the global markets under consideration. This strikes out any feedback effect in the model formulated under Section (2.4). The evidence is limited in contradiction

[24] To some extent, the choice of a quantile is arbitrary. However, Baur and McDermott (2010) and Hood and Malik (2013) all used the same quantiles.
[25] See Alagidede (2010) on Africa's financial markets integration.

of this assumption. The possibility of even weak feedback effect may be present for developed markets in Europe, North America, and or some parts of Asia with sizeable numbers of companies or institutional investors who have large holdings in the commodity markets.

We dwell on Equation (*2.4.1*) to examine the hedge and diversification hypotheses. If any of the parameters $d_1, d_2, and\, d_3$ is significantly different from zero, there is evidence of a non-linear relationship between an African stock and returns on commodities. Evidence of non-linear relationship shows how investors react differently to extreme market conditions relative to tranquil periods. A significant non-positive $d_0, d_1, d_2, or\, d_3$ indicates that African stocks are weak diversifiers for the variable under consideration. If any of the parameters $d_1, d_2, or\ d_3$ is negative and significantly different from zero, then African equities in the model can be described as having a strong diversification property. An African equity can act as a hedge if the parameter d_0 is zero (weak hedge) or significantly negative (strong hedge) and the sum of the parameters d_1 to d_3 are not jointly positive exceeding the value of d_0. Further, we specify a univariate GARCH (1,1) model to account for heteroscedasticity in the data as shown in Equation (2.4.2).

2.4 Empirical results

2.4.1 Preliminary analysis

Table 2.2 shows results of unit root test and summary features of all returns series. Panels A and B respectively refer to the full sample and sub-sample (GFC) periods. From the Augmented Dickey-Fuller (ADF) unit roots results shown in the last column, it is observed that all series are stationary at first difference. The distributional properties of the series show extreme behavior. The returns series are characterized by excess kurtosis for all variables and across sample periods. All series are positively skewed except Namibia, Mauritius, Ghana, Cote d'Ivoire, Botswana, and Oil (in the full sample period); and Kenya, Cote d'Ivoire, Oil, Gold, and Cocoa (in the crisis period). The assumption of normality for the series is also rejected by the JB statistic at the 1% significance level across the samples. The daily average mean returns and standard deviations (SDs) show relatively similar magnitudes in both the full and GFC period differentiated by the higher numbers of negative mean returns in the GFC period. Generally, the mean returns and SDs are respectively low and high for the commodities relative to the African stocks in both periods. Of this, gold and oil possess the

Table 2.2: Summary statistics of daily returns

	Mean (%)	SD (%)	Skewness	Kurtosis	JB @ 1% Sign. level	Sharpe Ratio (%)	ADF @ 1% Sig.
Panel A: *Full sample period* (03/01/2003 – 29/12/2014)							
TUNISIA	0.0389	0.6973	-0.1931	8.7326	4196.634	0.0558	Y
SOUTH AFRICA	0.0463	1.8240	-0.2636	8.6211	4052.103	0.0254	Y
NIGERIA	0.0254	1.3229	-0.2992	8.4972	3887.203	0.0192	Y
NAMIBIA	0.0549	1.2676	1.2366	50.4353	287198.4	0.0433	Y
MOROCCO	0.0155	1.3147	-0.0691	7.4497	2522.765	0.0118	Y
MAURITIUS	0.0511	0.8613	0.0168	15.7450	20676.83	0.0593	Y
KENYA	0.0377	1.1784	-0.0298	24.2293	57368.81	0.0320	Y
GHANA	0.0226	1.0095	0.8322	39.8584	173283.2	0.0224	Y
EGYPT	0.0804	1.8002	-0.6109	10.2633	6905.414	0.0447	Y
COTE D'IVOIRE	0.0681	1.3606	4.0323	58.6650	402704.7	0.0501	Y
BOTSWANA	0.0282	1.0004	1.7613	62.2022	447723.9	0.0282	Y
SILVER	0.0409	2.1162	-0.8063	9.0775	5026.128	0.0193	Y
PLATINUM	0.0239	1.4197	-0.7734	8.6216	4321.624	0.0168	Y
OIL	0.0186	2.3819	0.0391	13.5518	14231.71	0.0078	Y
GOLD	-0.0028	2.1457	-0.0824	9.8936	6052.505	-0.0013	Y
COCOA	0.0123	1.9338	-0.3544	18.8676	32113.48	0.0064	Y
S&P 500	0.0269	1.2166	-0.3313	14.7161	17505.98	0.0221	Y
BCOM	-0.0037	1.1164	-0.2570	5.5069	833.58	-0.0033	Y
MSCI-W	0.0245	1.0442	-0.4695	12.6210	11894.69	0.0235	Y
Panel B: *Crisis-period* (16/09/2008 – 01/06/2009)							
TUNISIA	0.0011	0.7798	-0.3042	9.3248	2693.23	0.0014	Y
SOUTH AFRICA	0.0181	2.0176	-0.2045	9.1625	2544.48	0.0089	Y
NIGERIA	-0.0581	1.4302	-0.3637	6.6739	935.71	-0.0406	Y
NAMIBIA	0.0395	1.1479	-0.3661	8.8703	2334.60	0.0344	Y
MOROCCO	-0.0825	1.4715	-0.0826	6.7579	943.88	-0.0561	Y
MAURITIUS	0.0094	0.9255	-0.3085	16.5319	12240.42	0.0102	Y
KENYA	-0.0055	0.9865	0.6173	13.7736	7844.57	-0.0056	Y
GHANA	-0.0029	1.0439	-0.3906	11.1584	4480.73	-0.0028	Y
EGYPT	-0.0113	1.8501	-0.9584	12.0904	5757.57	-0.0061	Y
COTE D'IVOIRE	0.0190	1.1912	0.1816	9.6950	2998.90	0.0160	Y
BOTSWANA	-0.0004	0.8624	-0.5772	7.5719	1483.23	-0.0055	Y
SILVER	0.0182	2.2568	-0.5526	8.9463	2440.23	0.0081	Y
PLATINUM	-0.0070	1.4855	-0.8493	8.5663	2259.34	-0.0047	Y
OIL	-0.0390	2.5492	0.7987	17.4152	14032.03	-0.0153	Y
GOLD	-0.0373	2.3803	0.0147	10.9640	4231.03	-0.0157	Y
COCOA	0.0097	1.7067	0.0043	6.1948	680.90	0.0057	Y
S&P 500	0.0280	1.4566	-0.3441	13.0513	6771.00	0.0192	Y
BCOM	-0.0151	1.1049	-0.0857	5.8708	551.72	-0.0137	Y
MSCI-W	0.0153	1.2623	-0.4575	10.8002	4114.59	0.0121	Y

Notes. *JB is the χ^2 statistic for testing normality. SD denotes standard deviation, and ADF is the augmented Dickey-Full test for unit root.* ***Y="yes"*** *indicating that the series is first-differenced stationary at the 0.01 significance level.*

highest SDs in both periods. Buyuksahin and Robe (2014) and Creti *et al.,* (2013) similarly observe that the rate of return on equities is generally less volatile than that on commodities. This may be partly due to the fact that prices of commodities (especially gold and oil) reflect the real-time equilibrium between demand and supply, with contingencies that change on daily basis.

The standard postulate in finance theory is that expectations for greater returns from an investment should be accompanied by the willingness to bear correspondingly higher risk; and the reverse holds. However, the risk/reward trade-off strikes the balance between the anticipation for the lowest possible risk and the highest possible return. We use the daily reward-to-variability ratio, also called the Sharpe ratios (SR) computed as the ratio of mean return to standard deviation for the measure of risk-reward trade-off for international investors. We observe from Table 2.2 that the SRs are positive for all series in the full sample period except gold and BCOM. However, the advent of the GFC (crisis period) renders the SRs of about ten assets (6 African stocks and 4 commodities) negative. Assets with negative/lower SRs show underperformance or higher risk bearing. The highest SRs are recorded for equities in Africa: Tunisia (5.6%), Mauritius (5.9%), and Cote d'Ivoire – (5.0%) - all in the full sample period.

In *Appendix 2A* we report results of autoregressive conditional heteroscedasticity (ARCH) test for examining the null of "no ARCH" effects and Ljung-Box test. Except for Botswana, Cote d'Ivoire and Ghana, we can reject the null of "no ARCH" effect for all other series. The presence of ARCH effect makes the estimation of a GARCH-type model more appropriate in modeling conditional correlation among the variables. The Ljung-Box test statistics identifying the presence of autocorrelation indicates the existence of significant temporal linear dependencies at the 1% significance level for most of the variables.

Figure 2.0 displays a visual inspection of the series over time from January 2003 to end of December 2014. Except for Ghana, Cote d'Ivoire, Botswana, and Namibia in which volatility clustering intensifies after 2009, all other markets show clustering across the entire sample period. Though the series are observed to be characterized by periodic breaks and variance concentrations, one can easily notice similar observable features between 2008 and 2009. This can be attributed to the GFC that sparked fluctuations in the prices/indices of most asset classes across the globe. Since volatility patterns of the series are seen to vary over time, we will conduct the Engle (2002) dynamic condition correlation (DCC) to empirically determine the level of time varying correlations among the variables.

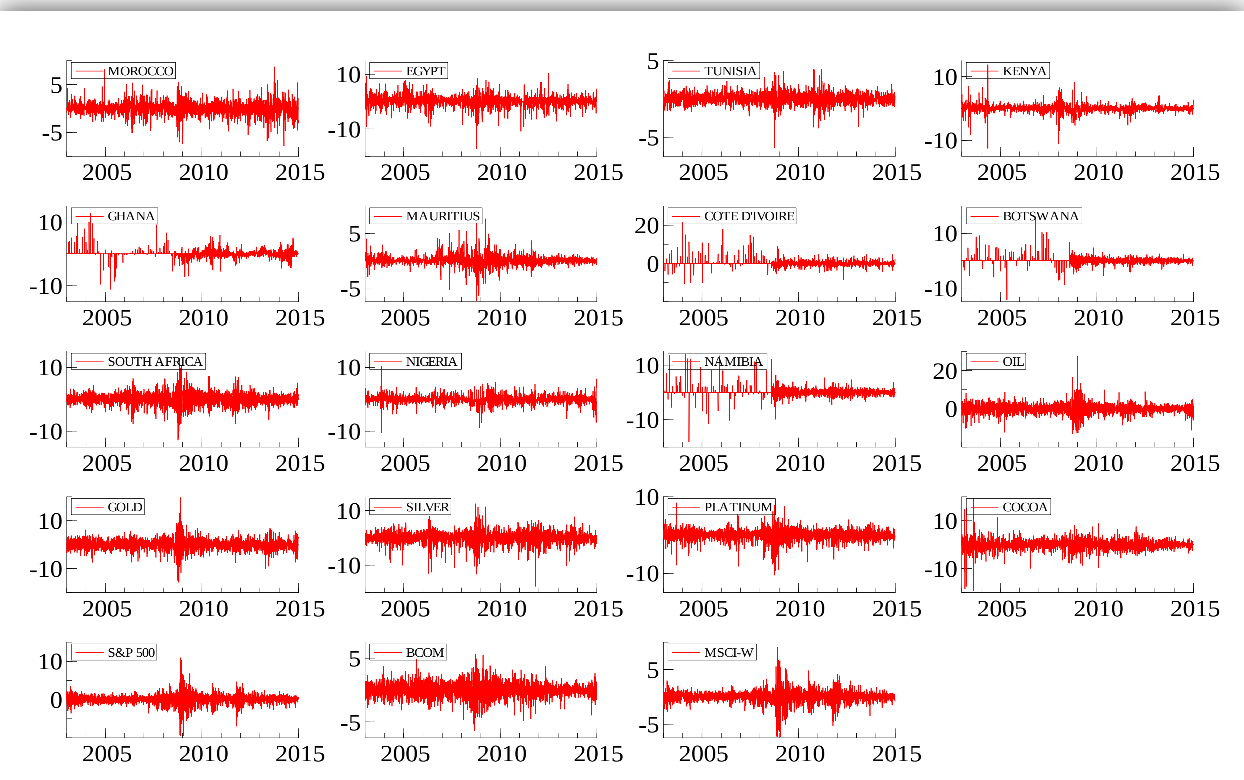


Figure 2.0: Time plots of all returns series

An important part of this study is how the African stocks behave relative to the commodities and global markets in their worst 10% (0.1), 5% (0.05), and 1%(0.01) performing days. These behaviours of the asset classes are reported in Table 2.3. Generally, it can be observed that although on the worst 1% days of the commodities and global markets average daily returns are lower than those of most of the African equity markets, they all yield positive returns. The same directional movement (or same sign) of the assets classes condenses any diversification opportunities. However, a more robust test for the hedging and diversification hypothesis can be achieved by executing the econometric model in Equations (2.4 and 2.4.1).

Table 2.3: Assets behaviour in falling commodity and global markets

Variables	Quantiles		
	0.10(%)	0.05(%)	0.01(%)
MOROCCO	25.68	17.21	8.82
EGYPT	42.35	31.17	15.61
TUNISIA	15.79	11.62	6.58
KENYA	23.49	17.50	9.06
GHANA	17.96	14.04	7.27
MAURITIUS	19.61	15.21	8.91
COTE D'IVOIRE	25.05	19.84	11.90
BOTSWANA	17.71	13.52	7.36
SOUTH AFRICA	37.99	26.39	11.66
NIGERIA	26.67	18.18	7.49
NAMIBIA	24.14	18.65	11.04
OIL	44.55	29.56	10.89
GOLD	38.25	24.63	8.08
SILVER	44.84	31.08	13.36
PLATINUM	29.72	20.56	8.50
COCOA	36.19	24.16	9.36
S&P 500	25.03	17.86	8.09
BCOM	20.51	12.91	3.79
MSCI-W	21.88	15.59	7.22

The table presents the average returns of all assets for the worst 10%, 5%, and 1% days. Sample is made up of 3056 daily returns on a close-to-close basis from 3rd January 2003 to 29 December 2014.

2.4.2 The excess market model analysis

The estimated CAPM model in Equation (2.1) provides a standard approach for assessing the risk associated with investing in African stock markets with respect to the global market indices (i.e. S&P 500, BCOM, and MSCI-W). Equation (2.1) is estimated for all eleven African stock markets in a static framework. The country by country estimation results together with two measures of risk-adjusted performance are shown in Table 2.4. The empirical results are discussed as follows.

Although, the Shape-Lintner version of the CAPM suggests that the Jensen's alpha (the intercept or constant term) should be zero, it can be observed from Table 2.4 that the country-by-country constants are negative (less than zero) and significant at the 1% level. The results suggest that during the 12-year period, investments in the African stocks underperformed those in the global markets; making African stocks generally less attractive to foreign investors at normal periods.

Results from the estimated beta (β_1) indicating the sensitivity of the African stocks to the market-wide source of risk (systematic risk) possibly arising from global markets volatility confirms the signs and magnitude of the Jensen alphas. Results relating to the dummy, D_t representing the effect of the GFC (β_2) indicates that the performances of all markets were negatively affected by the GFC at varying significance levels with S&P 500 as the benchmarked global market. With the Bloomberg Commodity Index as the global market, significant positive effects are noticed except for Botswana, Egypt, Ghana, Kenya, and Nigeria. Similarly, in the case of the MSCI-W, only Nigeria and Ghana are seen to have escaped the effects of the financial crisis. The above results suggest that depending on which global asset is under consideration, the effect of the crisis is uneven. The differences in the effects from the global assets may be accounted by differences in their compositions. For instance, although the S&P 500 and MSCI-W indexes are value-weighted and computed with dividends re-invested, the MSCI-W index reflects assets of both developed and emerging markets; and is more similar to widely quoted country index returns (Harvey, 1991). This posits that the African country index returns are more comparable to the MSCI-W returns than the S&P 500 returns, which reflects only U.S-based assets.

Further to the static model is the examination of some risk adjusted performance of the African equities relative to the benchmark global markets (i.e. S&P 500, BCOM, and MSCI-W) presented in columns 6-9 of Table 2.4. The market cycle comparisons are done on the basis of tracking errors (TRs) and information ratios (IRs) of the African stocks. First, the tracking error or active risk computed as the variance of the standard deviation of Africa's equities and the benchmark's returns aids in addressing the question of how much returns on African stocks, on average deviated from that of the benchmark during the full-sample and GFC periods. A lower TR indicates the proximity of the two returns and less risk.

It is clear from Table 2.4 that across all benchmarks and the two sample periods, Tunisia and South Africa recorded the lowest and highest TRs, respectively. South Africa's highest TR means that diversifying across the FTSE/JSE (Johannesburg Stock Exchange) in the 12 year period was riskier than across other African markets. Since TRs fail to establish outperformance and underperformance, it is unclear at this point whether the additional risk was worth it for international investors who decided to include South African stocks in a diversified portfolio. The IR rather helps in addressing this puzzle. The IR is defined as the quotient of the asset's (African stock) average mean excess returns relative to the benchmark's average mean return and the variability of that excess return. It helps to ascertain how much excess returns are generated for a unit additional risk taken with the inclusion of an African stock in a diversified portfolio relative to the benchmark.

A critical observation from the results suggest that any additional risk tolerated for investing in the South African equity market in both the full-sample and GFC periods was not worth it since the IRs are highly anemic compared to other markets, and international standards.[26] It thus appears that the Egyptian market offers a better alternative with slightly similar TRs in the full sample period as that of South Africa and higher IRs than South Africa. However, during the GFC, the Egyptian market records negative IRs with the BCOM and MSCI-W benchmarks. The African equities record relatively large numbers of negative IRs with the S&P 500 and MSCI-W as benchmark portfolios. This supports the findings of Goodwin (2009) that managers who benchmark against the S&P 500 index obtain lower IRs.

Next, we present results of the augmented market model in Table 2.5 where the impact of the global factors and the crisis on the African markets are estimated. The findings are discussed as follows. Analogous to the static market model results, the constant terms (α_0) are all negative and significant. Again, the African stocks underperform average returns on related global investments. It is informative to note that only Morocco, Ghana, Namibia, and Tunisia are dependent on changes in the market-wide returns (as measured by δ_0), during the GFC period. For all stocks, the betas are positive during full-sample period (β_0^*) and negative during crisis era (β_1^*). The inference is that the ability of African stocks to shield international portfolio investors from adverse shocks, during the crisis was minimal. Simatele (2014) reports that the most immediate effect of the GFC on Africa's equity markets was the flight of portfolio investments, mainly on account of increased risk aversion, tighter global credit conditions, and developments in the bond markets.

[26] The widely accepted IRs for performance superiority within the investment profession are 0.2 and 0.3 (Kidd, 2011). See also Grinold and Kaln (1995).

Table 2.4: Estimation results of the static market model and risk-adjusted performance measures

Market	Static Market Model Results (*full sample period with D_t*) – Eqn. 2.1				Risk-Adjusted Performance Measures			
					Full Sample Period		***Crisis Period***	
	β_0	β_1	β_2	DW	Tracking Error	Information Ratio	Tracking Error	Information Ratio
Panel A: S&P 500 as the benchmark global market								
BOTSWANA	-0.418[-13.212]***	0.686[49.539]***	-0.656[-20.451]***	2.03	0.974	0.002	0.834	-0.039
COTE D'IVOIRE	-0.327[-9.158]***	0.727[47.243]***	-0.730[-19.039]***	2.01	1.334	0.032	1.163	-0.008
EGYPT	-0.370[-7.659]***	0.682[33.225]***	-0.590[-12.243]***	2.01	1.774	0.031	1.822	-0.022
GHANA	-0.44[-12.707]***	0.671[-44.105]***	-0.671[-20.897]***	2.08	0.983	-0.003	1.016	-0.030
KENYA	-0.345[-7.975]***	0.425[26.076]***	-0.267[-8.506]***	2.02	1.152	0.010	0.958	-0.035
MAURITIUS	-0.299[-9.588]***	0.459[33.898]***	-0.372[-13.997]***	2.02	0.835	0.030	0.897	-0.021
MOROCCO	-0.452[-12.074]***	0.669[41.745]***	-0.616[-16.530]***	2.03	1.289	-0.008	1.443	-0.077
NAMIBIA	-0.331[-9.417]***	0.734[48.266]***	-0.747[-20.141]***	2.01	1.242	0.023	1.120	0.010
NIGERIA	-0.487[-9.098]***	0.352[19.882]***	-0.216[-6.761]***	2.02	1.296	-0.001	1.402	-0.061
SOUTH AFRICA	-0.342[-7.551]***	0.734[37.806]***	-0.799[-16.238]***	2.00	1.797	0.011	1.989	-0.005
TUNISIA	-0.310[-10.212]***	0.373[31.203]***	-0.375[-16.472]***	2.03	0.671	0.020	0.752	-0.036
Panel B: Bloomberg Commodity Index as the benchmark global market								
BOTSWANA	-0.308[-8.705]***	0.393[26.636]***	0.165[1.381]	2.03	1.004	0.032	0.877	0.012
COTE D'IVOIRE	-0.435[-10.642]***	0.629[37.941]***	0.243[1.715]*	2.02	1.364	0.053	1.206	0.028
EGYPT	-0.451[-8.547]***	0.606[29.181]***	0.218[1.180]	2.02	1.804	0.047	1.865	0.002
GHANA	-0.266[-7.083]***	0.389[26.588]***	-0.151[-1.185]	2.04	1.013	0.026	1.059	0.012
KENYA	-0.365[-7.796]***	0.373[24.282]***	0.103[0.641]	2.02	1.182	0.035	1.001	0.010
MAURITIUS	-0.367[-9.645]***	0.372[28.684]***	0.221[1.710]*	2.04	0.865	0.063	0.940	0.021
MOROCCO	-0.585[-13.540]***	0.565[33.173]***	0.455[3.014]***	2.06	1.318	0.015	1.486	-0.045
NAMIBIA	-0.516[-11.926]***	0.591[34.298]***	0.549[3.642]***	2.05	1.271	0.046	1.163	0.047
NIGERIA	-0.613[-9.540]***	0.264[15.464]***	0.174[0.783]	2.04	1.326	0.021	1.445	-0.030
SOUTH AFRICA	-0.421[-8.532]***	0.662[33.359]***	0.355[2.077]**	2.01	1.827	0.027	2.032	0.016
TUNISIA	-1.171[-11.050]***	0.065[5.172]***	0.677[1.870]*	2.69	0.701	0.061	0.795	0.020
Panel C: Morgan Stanley Capital International World Index as the benchmark global market								
BOTSWANA	-0.322[-9.383]***	0.378[23.227]***	0.322[2.749]***	2.02	0.976	0.008	0.847	-0.023
COTE D'IVOIRE	-0.431[-10.570]***	0.649[38.977]***	0.369[2.596]***	2.01	1.336	0.033	1.176	0.003
EGYPT	-0.446[-8.535]***	0.625[29.717]***	0.339[1.851]*	2.01	1.775	0.032	1.834	-0.015
GHANA	-0.290[-7.932]***	0.417[25.293]***	0.017[0.139]	2.03	0.985	-0.002	1.028	-0.018
KENYA	-0.419[-8.866]***	0.361[20.711]***	0.276[1.703]*	2.01	1.154	0.012	0.971	-0.021
MAURITIUS	-0.348[-9.797]***	0.376[26.994]***	0.339[2.786]***	2.03	0.837	0.032	0.910	-0.006
MOROCCO	-0.538[-12.980]***	0.616[36.703]***	0.540[3.733]***	2.03	1.290	-0.007	1.456	-0.067
NAMIBIA	-0.464[-11.305]***	0.646[38.693]***	0.635[4.432]***	2.03	1.243	0.024	1.132	0.021
NIGERIA	-0.588[-9.647]***	0.290[15.749]***	0.261[1.231]	2.02	1.298	3.03e-05	1.414	-0.052
SOUTH AFRICA	-0.410[-8.364]***	0.688[34.431]***	0.482[2.821]***	2.00	1.799	0.012	2.002	0.001
TUNISIA	-1.103[-11.518]***	0.087[6.347]***	0.722[2.167]**	2.65	0.673	0.022	0.764	-0.019

****, **, * denote statistical significance at the 0.01, 0.05, and 0.1 levels respectively. Figures in parenthesis [] represent test statistics. DW is the Durbin-Watson statistic indicating the absence of any remaining autocorrelation in the series.*

Baur and McDermott (2010) have observed that relative to developed markets, emerging markets fail to provide protection for traditional assets (such as stocks and bonds) during global market turmoil. The plausible reason may be that increased global market uncertainties during extreme periods casts a shadow of doubt on the potentials of emerging markets to offer higher expected rewards. Fueled by market uncertainty, investor sentiments and risk-aversion, international portfolio investors may pull out their holdings in African equities during crisis periods leading to greater impact. Instead, on the balance of probability of success, they may prefer to shift their portfolios towards the relative safety of developed world markets (Baur and McDermott, 2010). *Whilst the above constitute a somewhat simplistic intuitive approach to explaining the dynamics, its plausibility is intact.*

The negative effects of the GFC on African markets could also be attributed to the effects on trade balances possibly arising from export demand shocks and price movements of key commodities. In most of the African economies, example South Africa, the spillover effects was also felt through a deteriorating overall economy (Simatele, 2014). The slump in the economic aggregates registered heightened pressure on individual country's balance of payment with consequential effects on domestic exchange rates, overall gross domestic product (GDP) and financial sectors, without corresponding increases in portfolio investments flows. For instance, at the peak of the crisis in 2008, no African country issued bonds and already existing ones were either cancelled or postponed (Kasekende *et al.,* 2009; Brambila-Macias and Massa, 2010).

Results for the commodities in both the full and GFC periods vary from market to market. A dollar increase in the price of gold is seen to exert significant positive effects on the average returns of six African stock markets in the two regimes. The effects of oil price increases are positive for the affected markets in the full-sample period. However, some negative effects are recorded in the crisis periods for Mauritius, Cote d'Ivoire, and Ghana. Rising cocoa prices have significant positive effects on the average daily returns of Kenya, Mauritius, Nigeria, and South Africa in the post-crisis era. The effect of silver on the markets is noticeable in the GFC periods, and that it is negative for Kenya and positive for Mauritius.

2.4.3 African markets correlations with commodities and world markets

Although returns distributions of African markets appear highly volatile (Moss and Thuotte, 2013), adding securities from Africa into a diversified global portfolio can reduce overall portfolio risk

(Alagidede, 2008). Intuitively, as the number of equity securities in a portfolio increases, the return variance of the entire portfolio (irrespective of individual securities variances) should decrease in as much as the correlations between securities are low-positive or negative. With the DCC-GARCH model, we seek to examine hedging and diversification opportunities across the eleven African markets. To address this, we calculate time-varying return correlations between individual African stock markets and each of the commodities and global indices in our sample for both the full sample and crisis periods. For conservation of space, we report only stage two results of the DCC-GARCH model estimation (though results of stage one is available upon request). We show the stage two results for the full sample and post-crisis periods in Tables 2.6 and 2.7, respectively.

Close observations of the results in both tables generally show similar patterns of correlations between the African stocks and global commodities, since all significant correlations are non-negative, except that between Ghana and oil (see Table 2.7). However, the magnitudes of the correlation coefficients from markets to markets and across regimes (i.e. full sample and sub-sample) do not show any definite pattern to warrant trend analysis. The coefficients associated with the ARCH (ϕ_1) and GARCH (ϕ_2) parameters similarly show mixed results. However, very few of them follow some patterns.

It appears clear that in the full sample period, the ARCH and GARCH parameters are highly significant for the following market pairs: Morocco-gold; Egypt-oil; Tunisia-oil, gold; Kenya-BCOM; Ghana-gold; South Africa-gold, oil; Nigeria-cocoa; and Namibia-oil, gold. Similarly, in the sub-sample period, the correlations between Morocco-gold, oil; Tunisia-gold, oil; Mauritius-cocoa; South Africa-gold, oil; Cote d'Ivoire-oil; and Botswana-gold, oil; show substantial volatility persistence. The generally small sizes of the ARCH coefficients suggest slow changing conditional volatilities under the effects of return innovations. They however evolve with time on the effects of past volatility, as indicated by the close to unity GARCH coefficients in many instances.

Table 2.5: Augmented market model results (full sample period).

The regressors GOLD, OIL, COCOA, SILVER, PLATINUM, respectively relate to the coefficients $\alpha_1, \delta_1; \alpha_2, \delta_2; \alpha_3, \delta_3; \alpha_4, \delta_4$; and α_5, δ_5. α_0 is the intercept, and β_0^*, β_1^* are the coefficients for the excess global markets in the full-sample and sub-sample periods respectively.

Market	α_0	β_0^*	α_1	α_2	α_3	α_4	α_5	δ_0	β_1^*	δ_1	δ_2	δ_3	δ_4	δ_5	*DW*
Panel A: S&P 500 as the global market															
BOTSWANA	-0.41***	0.70***	0.04***	0.03***	0.01	0.00	-0.00	0.12	-0.66***	0.05*	-0.00	0.06	0.00	-0.01	2.02
COTE D'IVOIRE	-0.32***	0.73***	0.05***	0.02	0.01	0.02	-0.00	-0.03	-0.73***	0.07**	-0.04	-0.01	0.02	-0.00	2.00
EGYPT	-0.37***	0.68***	0.01	0.03	-0.00	0.02	-0.00	0.03	-0.59***	0.11***	-0.02	0.10	0.03	0.02	2.01
GHANA	-0.42***	0.69***	0.01	-0.01	0.00	0.02	0.00	-0.17	-0.69***	0.01	-0.22	-0.01	-0.03	-0.01	2.07
KENYA	-0.36***	0.42***	0.01	0.01	0.00	-0.00	0.01	0.09	-0.27***	0.00	-0.02	0.14***	-0.05**	-0.06*	2.02
MAURITIUS	-0.32***	0.45***	0.01	-0.00	-0.00	0.01	0.02*	0.12	-0.36***	0.10***	-0.06***	0.17***	0.12***	0.02	2.02
MOROCCO	-0.46***	0.68***	0.07***	0.03**	-0.01	0.01	0.04*	0.22*	-0.62***	0.06*	-0.03	-0.00	0.02	-0.07	2.02
NAMIBIA	-0.34***	0.74***	0.07***	0.05***	0.02	0.00	0.00	0.26**	-0.74***	0.06**	0.04	0.01	0.02	0.00	2.01
NIGERIA	-0.49***	0.35***	-0.02	0.01	-0.00	0.01	-0.02	0.10	-0.21***	-0.01	-0.03	0.08**	-0.01	0.05	2.02
SOUTH AFRICA	-0.28***	0.78***	0.35***	0.10***	0.02	0.01	0.00	0.05	-0.83***	0.01	0.10***	0.12**	-0.00	0.06	1.99
TUNISIA	-0.33***	0.37***	0.05***	0.03***	-0.01	0.00	-0.01	0.17	-0.37***	-0.01	0.02	0.01	-0.00	0.01	2.05
Panel B: Bloomberg Commodity Index as the global market															
BOTSWANA	-0.28***	0.43***	0.03**	0.04***	0.01	0.00	-0.01	0.07	-0.29***	0.05**	-0.03	0.05	0.00	0.01	2.03
COTE D'IVOIRE	-0.36***	0.68***	0.03**	0.03*	0.01	0.01	-0.02	0.03	-0.60***	0.08**	-0.05*	-0.02	0.02	0.02	2.01
EGYPT	-0.36***	0.67***	0.00	0.03*	0.00	0.01	-0.02	-0.00	-0.63***	0.11***	-0.03	0.09	0.03	0.03	2.01
GHANA	-0.23***	0.44***	0.00	-0.00	0.01	0.01	-0.00	-0.28**	-0.39***	0.02	-0.05**	-0.01	-0.01	0.01	2.03
KENYA	-0.35***	0.38***	0.01	0.01	0.01	-0.01	0.01	0.07	-0.06	0.02	-0.01	0.12***	-0.07***	-0.04	2.00
MAURITIUS	-0.33***	0.41***	0.01	-0.00	0.01	0.01	0.02	0.08	-0.33***	0.12***	-0.05***	0.15***	0.12***	0.04	2.04
MOROCCO	-0.50***	0.63***	0.06***	0.04***	-0.01	0.01	0.03	0.26*	-0.49***	0.06*	-0.03	-0.01	0.01	-0.05	2.04
NAMIBIA	-0.41***	0.66***	0.06***	0.06***	0.02	0.00	-0.02	0.35**	-0.58***	0.07**	0.04	-0.01	0.01	0.02	2.03
NIGERIA	-0.56***	0.30***	-0.02	0.02	0.00	0.01	-0.01	0.08	-0.22***	0.01	-0.02	0.07*	-0.02	0.06*	2.04
SOUTH AFRICA	-0.31***	0.74***	0.33***	0.11***	0.02	0.00	-0.01	0.13	-0.63***	0.02	0.10***	0.10*	0.00	0.08	2.00
TUNISIA	-0.04***	0.16***	0.06***	0.03***	-0.01	-0.00	0.00	0.01	-0.20***	0.01	0.01	-0.03	-0.01	-0.02	2.19
Panel C: Morgan Stanley Capital International World Index as the global market															
BOTSWANA	-0.33***	0.75***	0.04***	0.03**	0.01	-0.00	-0.02	0.01	-0.78***	0.05*	-0.00	0.05	0.01	-0.00	2.02
COTE D'IVOIRE	-0.27***	0.77***	0.05***	0.02	0.01	0.01	-0.02	-0.09	-0.80***	0.07**	-0.04	-0.01	0.02	0.01	2.00
EGYPT	-0.30***	0.73***	0.01	0.03	0.00	0.01	-0.01	-0.06	-0.70***	0.11***	-0.02	0.09	0.03	0.03	2.00
GHANA	-0.31***	0.76***	0.01	-0.02	0.01	0.01	-0.01	-0.27**	-0.74***	0.01	-0.02	-0.01	-0.02	0.00	2.04
KENYA	-0.32***	0.47***	0.02	0.00	0.01	-0.02*	-0.00	0.03	-0.41***	0.02	0.01	0.14***	-0.07**	-0.05	1.99
MAURITIUS	-0.27***	0.47***	0.01	-0.01	0.01	0.00	0.02	0.09	-0.39***	0.11***	-0.02	0.17***	0.10***	0.03	2.02
MOROCCO	-0.39***	0.73***	0.07***	0.03**	-0.01	0.01	0.03	0.16	-0.64***	0.05*	-0.03	-0.01	0.02	-0.06	2.02
NAMIBIA	-0.28***	0.78***	0.07***	0.05***	0.02	-0.00	-0.01	0.19	-0.80***	0.06**	0.04*	-0.00	0.02	0.02	2.01
NIGERIA	-0.45***	0.40***	-0.01	0.01	0.00	-0.00	-0.02	0.03	-0.36***	0.00	0.01	0.08**	-0.02	0.06	2.00
SOUTH AFRICA	-0.23***	0.82***	0.35***	0.10***	0.02	0.00	-0.01	0.02	-0.81***	0.01	0.10***	0.11*	0.01	0.08	1.99
TUNISIA	-0.35***	0.44***	0.06***	0.02***	-0.00	-0.01	-0.02	0.33***	-0.39***	-0.01	0.03**	0.01	-0.00	0.01	2.09

*Note: ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively; and DW is the Durbin-Watson statistics indicating the absence of any remaining autocorrelation in the series. δ_0 is the parameter capturing the effect of the GFC.*

Table 2.6: Dynamic conditional correlation results (*full sample period*)

	OIL	GOLD	SILVER	PLATINUM	COCOA	BCOM
MOROCCO						
ρ	0.120***	0.171***	0.014	0.042**	0.014	0.028
ϕ_1	0.009	0.013**	0.000	0.012	0.000	0.018
ϕ_2	0.981***	0.979***	0.832	0.799***	0.844	0.720
L-L	-11374.27	-11119.31	-11243.04	-9927.99	-10944.53	-9263.93
AIC	7.45	7.198	7.221	6.340	6.961	6.072
EGYPT						
ρ	0.057***	0.043*	0.006	0.006	0.020	0.029
ϕ_1	0.017*	0.007	0.011	0.000	0.000	0.000
ϕ_2	0.813***	0.960***	0.949***	0.840	0.858***	0.823***
L-L	-12464.55	-12242.89	-12311.03	-11001.52	-12014.47	-10335.34
AIC	7.937	7.827	7.792	6.982	7.525	6.773
TUNISIA						
ρ	0.156***	0.297	0.023	0.002	0.032	0.013
ϕ_1	0.007**	0.009**	0.010	0.017	0.014*	0.000
ϕ_2	0.983***	0.991***	0.728***	0.573***	0.961***	0.820
L-L	-9425.13	-9129.20	-9307.48	7996.03	-9003.43	-3898.74
AIC	6.103	5.932	6.008	5.175	5.756	4.884
KENYA						
ρ	0.014	0.046**	-0.023	0.004	0.036	0.006
ϕ_1	0.000	0.055**	0.000	0.018*	0.004	0.015*
ϕ_2	0.834**	0.000	0.840	0.000	0.989***	0.955***
L-L	-10543.46	10310.07	-10383.93	-9072.16	-10081.28	-4066.42
AIC	6.753	6.637	6.612	5.797	6.359	5.094
GHANA						
ρ	-0.011	0.023	0.025	0.015	0.025*	-0.005
ϕ_1	0.000	0.006*	0.000	0.000	0.000	0.000
ϕ_2	0.874**	0.982***	0.844	0.851*	0.863***	0.847***
L-L	-10723.73	-10496.06	-10563.92	-9252.49	-10265.41	-4339.34
AIC	6.306	6.192	6.053	5.285	5.723	5.435
MAURITIUS						
ρ	0.007	0.055***	0.035*	0.032	0.043**	0.031
ϕ_1	0.018	0.015	0.000	0.001	0.000	0.006
ϕ_2	0.778***	0.000	0.830	0.833	0.840**	0.886***
L-L	-9522.55	-9293.47	-9363.47	-8051.72	-9063.98	-3821.93
AIC	6.105	5.994	5.967	5.143	5.702	4.788
SOUTH AFRICA						
ρ	0.291***	0.452***	0.027	0.010	0.063***	0.002
ϕ_1	0.027*	0.021***	0.008	0.003	0.000	0.004*
ϕ_2	0.964***	0.975***	0.964***	0.993***	0.863***	0.988***
L-L	-12002.74	-11489.89	-12002.81	-10692.09	-11700.73	-10026.39
AIC	7.794	7.483	7.773	6.955	7.532	6.571

Table 2.6 continued.

	OIL	GOLD	SILVER	PLATINUM	COCOA	BCOM
NIGERIA						
ρ	0.019	-0.007	0.027	0.001	0.009	-0.013
ϕ_1	0.011	0.082***	0.000	0.049**	0.000***	0.000
ϕ_2	0.505	0.086	0.825***	0.000	0.859***	0.836***
L-L	-11189.31	-10954.31	-11029.97	-9715.79	-10731.91	-9053.89
AIC	7.259	7.133	7.121	6.288	6.872	5.934
NAMIBIA						
ρ	0.108	0.163	0.004	-0.008	0.042*	0.017
ϕ_1	0.014***	0.012***	0.007	0.000	0.020*	0.000
ϕ_2	0.985***	0.988***	0.968***	0.856	0.942***	0.868
L-L	-11440.72	-11195.23	-11362.22	-10051.79	-11058.57	-9386.52
AIC	6.791	6.658	6.626	5.867	6.298	6.152
COTE D'IVOIRE						
ρ	0.000	0.000	0.000	-0.000	0.000	-0.000
ϕ_1	0.000	0.000	0.000	0.004	0.059	0.000
ϕ_2	0.997***	0.999***	0.995***	0.979***	0.904***	0.961***
L-L	-35352.90	-35240.94	-34890.16	-33835.83	-34114.29	-33412.51
AIC	23.152	23.079	22.85	22.16	22.34	21.81
BOTSWANA						
ρ	0.000	0.000	-0.000	0.000	0.000	-0.000
ϕ_1	0.000	0.000	0.069	0.002	0.000	0.050
ϕ_2	0.999***	0.963***	0.912***	0.982***	0.999***	0.900***
L-L	-33152.18	-33040.21	-32689.43	-311635.11	-31913.58	-31211.78
AIC	21.711	21.638	21.408	20.718	20.900	20.441

Notes: *The table shows results of Engle (2002) DCC-GARCH (1,1) estimations. The model is estimated using the Student t-distribution.* ϕ_1 *and* ϕ_2 *are respectively the ARCH and GARCH parameters under the restrictive assumptions of non-negativity and* $\phi_1 + \phi_2 < 1$. *L-L is log-likelihood, AIC is the Alkaike information criterion, and* ρ *is a measure of correlation. ***, **, * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.*

On the basis of this, investors seeking to trade across the above indicated market pairs may have to focus on active investment strategies informed by volatility persistence and present market conditions. Advisedly, the proportion of portfolio investments may have to be increased (decreased) in bullish (bearish) markets. Additionally, such strategies must take into account the stability and performances of successive periods.

Table 2.7: Dynamic conditional correlation results *(Sub-sample period)*

	OIL	GOLD	SILVER	PLATINUM	COCOA	BCOM
MOROCCO						
ρ	0.171***	0.123**	-0.003	0.012	0.017	0.043
ϕ_1	0.015***	0.015**	0.000	0.006	0.000	0.038*
ϕ_2	0.973***	0.971***	0.830	0.817***	0.851	0.687***
L-L	-5966.056	-6119.365	-6169.93	-5459.704	-5761.456	-4974.11
AIC	7.468	7.658	7.721	6.834	7.211	6.227
EGYPT						
ρ	0.088***	0.035	-0.005	-0.036	0.014	0.035
ϕ_1	0.021	0.012*	0.003	0.000	0.000	0.000
ϕ_2	0.647***	0.953***	0.980***	0.841	0.843	0.831*
L-L	-6239.103	-6333.998	-6557.37	-5846.531	-6149.203	-5365.10
AIC	7.809	7.928	8.205	7.317	7.695	6.716
TUNISIA						
ρ	0.194***	0.168***	0.001	0.017	0.053	0.013
ϕ_1	0.012**	0.007**	0.008	0.031	0.011	0.000
ϕ_2	0.975***	0.988***	0.696***	0.382**	0.963***	0.820
L-L	-4890.523	-5027.761	-5090.26	-4327.991	-4677.674	-3898.74
AIC	6.124	6.295	78.65	5.422	5.857	4.884
KENYA						
ρ	0.038	0.059**	-0.026	-0.016	0.060**	0.006
ϕ_1	0.005	0.000	0.000	0.031*	0.026	0.015*
ϕ_2	0.967***	0.842	0.794*	0.000	0.731***	0.955***
L-L	-5182.915	-5224.53	-5178.72	-4500.305	-4848.662	-4066.42
AIC	6.488	6.540	6.484	5.637	6.071	5.094
GHANA						
ρ	-0.036*	-0.002	0.004	0.008	0.019	-0.005
ϕ_1	0.000	0.008*	0.000	0.000	0.000	0.000
ϕ_2	0.847	0.983***	0.857	0.853	0.828	0.847***
L-L	-5453.454	-5495.10	-5530.858	-4820.806	-5122.340	-4339.34
AIC	6.826	6.878	6.923	6.036	6.413	5.435
MAURITIUS						
ρ	0.030	0.058**	0.020	-0.016	0.058	0.031
ϕ_1	0.018	0.005	0.000	0.008	0.006**	0.006
ϕ_2	0.763***	0.866***	0.842	0.047	0.992***	0.886***
L-L	-4936.386	-4977.95	-4936.496	-4304.228	-4599.418	-3821.93
AIC	6.180	6.232	6.182	5.391	5.759	4.788
SOUTH AFRICA						
ρ	0.368***	0.269*	-0.006	-0.023	0.076*	0.002
ϕ_1	0.038***	0.020**	0.011	0.000	0.010	0.012
ϕ_2	0.946***	0.978***	0.930***	0.834	0.968***	0.856***
L-L	-6225.18	-6258.42	-6462.663	-5753.173	-6049.271	-5271.34
AIC	7.790	7.832	8.087	7.201	7.571	6.599

Table 2.7 continued.

	OIL	GOLD	SILVER	PLATINUM	COCOA	BCOM
NIGERIA						
ρ	0.010	-0.026	0.028	0.025	0.022	-0.009
ϕ_1	0.000	0.068***	0.000	0.053	0.000	0.000
ϕ_2	0.818***	0.042	0.816***	0.097	0.817***	0.820***
L-L	-5922.99	-5961.13	-5998.779	-5286.931	-5590.779	-4807.83
AIC	7.413	7.461	7.508	6.618	6.998	6.020
NAMIBIA						
ρ	0.255***	0.226**	-0.001	-0.008	0.065	0.018
ϕ_1	0.013**	0.014***	0.010	0.005	0.010	0.000
ϕ_2	0.978***	0.982***	0.825***	0.948***	0.974***	0.831*
L-L	-5566.60	-5590.33	-5722.066	-5012.029	-5308.344	-4530.54
AIC	6.967	6.997	7.162	6.275	6.645	5.673
COTE D'IVOIRE						
ρ	0.000	0.184***	-0.033	-0.009	0.038	-0.004
ϕ_1	0.000	0.041**	0.008	0.019	0.000	0.013
ϕ_2	0.997***	0.874***	0.840***	0.792***	0.813**	0.935***
L-L	-35352.9	-5828.30	-5892.921	-5183.210	-5484.573	-4700.93
AIC	23.152	7.295	7.375	6.489	6.865	5.886
BOTSWANA						
ρ	0.181**	0.174*	-0.027	-0.017	0.075*	-0.000
ϕ_1	0.008**	0.012**	0.020	0.000	0.008	0.006
ϕ_2	0.991***	0.987***	0.441	0.834***	0.985***	0.832***
L-L	-5164.45	-5203.82	-5298.147	-4588.84	-4883.328	-4107.522
AIC	6.465	6.514	6.632	5.746	6.114	5.145

See notes under Table 2.6

Focusing specifically on the correlation coefficients, our results suggest that African equity returns generally have low correlations with returns on commodities. Significantly low correlations imply the possibility of diversification opportunities across the African markets. Despite this, several factors remain as critical hindrances. First, the relatively nascent markets in Africa usually have small sizes, are illiquid and not diversified. For instance, the total market capitalization of SSA equity markets increased from US$605,113 million in 2005 to US$732,438 million in 2012. Of this, South Africa alone constituted US$565,408 million and US$612,308 million in 2005 and 2012, respectively. Even with this, the number of tradable shares (free floats) is usually small compared to the market capitalizations. Although, South Africa has the highest market capitalization to GDP ratio in the sub-region, it recorded reduced values from 2005 (219.3%) to 2012 (154.1). In SSA, total number of listed companies on all exchanges moved marginally from 911 (2005) to 923 (2012) compared to other emerging economies such as East Asia Pacific with 3,931 (5,311); South Asia: 6,050 (6,496); and Latin America and Caribbean: 1,092 (1,066) in years 2005 (2012) respectively. In a similar fashion, by 2012, turn-over ratios (values of traded shares as a percentage of market capitalization) in SSA markets increased slightly from 37.3% in 2005 to 47.2% in 2012, anemic to that of East Asia Pacific of 68.4% (2005) and 127.7% (2012). [27] Because the minimum trade requirements of many international institutional investors are $1-5 million per block (Moss *et al.,* 2005), transactions in African markets thus become too small to be considered for diversification.

Second, is the problem of exchange rate risk. A highly unstable local currency can have adverse consequential effects on the returns of investors in the domestic bourse. For instance, in the first two regimes of constitutional rule in Ghana from 1993 to 2000, returns on the Ghana stock market in local currency units averaged 43 percent relative to 5 percent for dollar-denominated returns following a highly depreciating local currency. Recently, Boako *et al.,* (2016) report of high dependence of the Ghana equity market on the foreign exchange market, and that the link between the two markets supports the international trade-oriented model. Aside the above challenges, constraints relating to poor governance structures, political unrest, high inflation, lack of proper securities regulation and supervision, macro-economic unsteadiness, and returns volatility are apparent.

The results further show that the average significant correlations in the full sample and post-crisis periods are 10.94 percent and 14.96 percent, respectively; with the number of recorded significant correlations being 15 (full sample) and 18 (post crisis) periods. The inference is that correlations did not only intensify after the crisis, but also spread.[28] The phenomenon may imply that opposing to the 'decoupling' view that African stock markets were insulated from shocks contagion during the GFC; the crisis may have led to some spillovers to the African stock markets. This supports Forbes and Rigobon's (2002) 'shift-contagion' theory – *of increases in cross-markets correlations during a crisis*. Intuitively, the effects of the spillovers may be higher in liquid markets than in thinner markets. Since, the focus of this chapter is not to examine the level of shocks spillovers, we defer that to subsequent chapters. Similar to Choi and Hammoudeh (2010) and Creti *et al.,* (2013), the results depict high volatilities for the correlations between the African equities and commodities indicated

[27] Figures are gleaned from World Development Indicators Database (2015) - http://wdi.worldbank.org/table/5.4, and the website of African Securities Exchanges Association 2015 - http://www.african-exchanges.org/yearly_statistic/comparative/.

[28] Moss and Thuotte (2013) observes time-varying increases in correlation and report that excluding South Africa and Mauritius, the correlation between Sub-Saharan African stocks and the S&P 500 were 0.343 in 2000-2007, 0.702 in 2007-2009, and 0.749 in 2009-2011.

in the previous paragraph. From the graphical plots of the conditional correlations (*though unreported due to space constraint but available upon request*) it is observed that the correlations become intense just at the time of the global financial crisis around 2008 and 2009.

Since most significant correlations and high volatility persistence were observed between African equities on one hand and each of gold and oil on the other hand, there is the need to shed some light on the development. First, it is important to note that oil and gold were observed to have the highest volatilities among the commodities and global indices considered in this study (see Table 2.2). The importance of oil in the development of financial markets can be registered in the litany of studies that focus on the relationship between oil and stock markets (see for example, Jones and Kaul, 1996; Bastianin and Manera, 2014, etc.). Theoretically, rising crude oil prices affect the prices of equities through either the discount rate or cash flow effect.

In this particular instance, rising crude oil prices (up to about $147 a barrel) in 2008 gradually increased firm's marginal costs of production in Africa resulting in significant losses. Since the value of a stock is a function of firms' expected future cash flows, losses in cash flows may have caused asset prices to decline in Africa. However, this could not drive the correlations between the African equities and crude oil prices to negative, limiting possible portfolio diversification effectiveness. As the crisis begun to ease from 2009 with the plummet of oil prices below the $100 mark, equity returns in Africa started to rise gradually as in the case of South Africa, Tunisia, Mauritius, and Cote d'Ivoire until somewhere in 2011 when oil prices started increasing slightly for a short period and assumed a stable trend. Equity prices then begun to move slowly along the level of increases for oil, hence the positive correlation. The rate of change of equity returns in Africa relative to shifts in crude oil prices, however, appears to be slow.

On the part of gold, literature has largely found evidence of negative correlation with asset classes supporting the safe-haven characteristics of gold (e.g. Baur and McDermott, 2010; Beckmann *et al.,* 2014). However, the rather positive relationship established for gold and some African stocks corroborates Baur and McDermott (2010) which found similar results for emerging markets, and Arouri *et al.,* (2015) for China. In view of the generally lower (less than 0.5) significant cross-market correlations between each of gold and oil on one hand and some of the African stocks on the other hand, it is natural to assume that having both asset pairs in a single portfolio may better the lot of investors. However, judging from the significant volatility cross-effects (shown in Tables 2.6 and 2.7), it will be more prudent for portfolio investors to estimate the prime weights and hedge ratios of African stocks in a considered hedged portfolio in order to suitably account for the prudence of the hedge.

2.4.4 Optimal hedge ratios (OHR) and portfolio weights of African stocks

A diversifier is an asset that is positively (but not perfectly correlated) with another asset or portfolio on average. Also provided correlation rises in absolute terms, increased correlations would mean that commodities/stocks can offer better diversification or hedging avenues (Oslon *et al.,* 2014). On the basis of this, we argue that since hedging entails taking a long position in one asset (as in stocks) and a short position in another (say a commodity), a surge in correlations means that price fall in the commodities futures/spot market would be better offset by a long position in the stock markets, thereby making the hedge effective. In view of the above and our week cross-market correlations found for gold and oil; and some African stocks, we proceed to examine the implications of the DCC-GARCH(1,1) results on stock-gold and stock-oil optimal portfolios. The objective is to derive a hedged portfolio in which the international investor seeks cover from exposure to gold or oil price declines with investment in African stock markets. In which case, the investor's prime objective is to maintain higher expected returns whilst minimizing risk.

For illustrative purposes, we assume the practical situation of an international oil firm seeking shield from Africa's equities away from exposure to price volatilities in the crude oil market. The hedge ratio on the oil firm's portfolio of African equities and crude oil position is defined as:

$$\gamma = \frac{r_{0il} - r_t}{r_s} \qquad [2.5]$$

where γ is the hedge ratio – *representing the dollar amount of crude oil that the hedger (oil firm) must short for each share price in Africa*; r_t is the return on holding the portfolio between *t-1* and *t*; r_s and r_{oil} are the returns on holding the equities and crude oil positions respectively, between *t* and *t-1*.

From the DCC-GARCH (Engle, 2002) model framework, the OHR is computed as:

$$\gamma_t^* \mid \Omega_{t-1} = \frac{h_{oil,s}}{h_s}, \qquad [2.5.1]$$

given that $h_{oil,s}$ and h_s are the conditional covariance of crude oil and stock returns; and conditional variance of stock returns respectively; and Ω_{t-1} is information available at *t-1*.

In order to establish the required optimal portfolio structure that minimizes risk subject to a no-shorting constraint, we apply Kroner and Ng (1998) methodology to compute the optimal holding weight (*w*) of African stocks in a $1 portfolio of stock/oil at time *t* as:

$$w = \frac{h_{s_t} - h_{(oil,s)_t}}{h_{oil,t} - 2h_{(oil,s)t} + h_{s,t}} \qquad [2.5.2]$$

where $h_{oil,t}$ is the conditional variance of crude oil returns at time *t*. All others are as defined in equation [2.5.1].

Assuming a mean-variance (MV) utility function in the absence of short-selling, the following constraint is imposed on the optimal weight of the stocks through optimization:

$$w_t^{oil,s} = \begin{cases} 0, & if \quad w_t^{oil,s} < 0 \\ w_t^{oil,s}, & if \quad 0 \le w_t^{oil,s} \le 1 \\ 1, & if \quad w_t^{oil,s} > 1 \end{cases}$$

where $\left(1 - w_t^{oil,s}\right)$ determines the proportion of dollar amounts that the investor puts into the crude oil market at time *t*.

We present results of the optimal hedge ratios, portfolio weights, and hedge effectiveness in Table 2.8. By way of strategy, an investor seeking to hedge his/her price risk in the crude oil or gold (hereafter referred to as OG) market would take a risk-minimizing position in order to realize the highest average expected return from the stock-OG portfolio. *Practically, taking a $1 long position in an African equity can be offset with a $ γ^* short position in the OG market.*

The optimal weights of Africa's equities in a stock-oil (so) and stock-gold (sg) portfolios effectively accentuate the cent amount of a $1 portfolio that should be allocated to a stock in Africa in order to minimize risk without lowering expected rewards. For instance, the 51.54% optimal weight for South Africa in the stock-oil portfolio (see Panel A) means that the proportion of the $1 portfolio to be allocated to the JSE/FTSE All-

Share-Index and oil are 51.54 and 48.46 cents, respectively. The results generally show that international oil and/or gold investors holding or seeking to hold assets in Africa, may have to allocate on average, about 50:50 weight each to an African stock and a commodity to be able to maximize their risk-return trade-off, since average optimal weights in both the full and sub-sample periods are respectively, 51.34% and 51.37%.

The optimal average hedge ratios are relatively low ranging from 0.0418 to 0.4452 in the full sample period and 0.0865 to 0.3709 in the sub-sample period. In all, South Africa and Egypt record the highest and lowest hedge ratios, respectively. The results indicate that in the full-sample period, a $1 long (buy) in the South African stock market (FTSE/JSE) should be accompanied by a short (sell) of 28.47 cents and 44.52 cents in the oil and gold spot markets, respectively. Analogously, in the sub-sample period, a $1 dollar buy in the FTSE/JSE should be shorted by 37.09 cents and 27.21 cents of oil and gold, respectively.

Though results from the optimal portfolio weights and hedge ratios indicate the relevance of including equities from Africa in stock-gold or stock-oil hedged portfolios, the critical question that remains unanswered is how effective the hedge would be to enhance the portfolio's risk-adjusted performance? This leads us to the examination of the hedging effectiveness of the portfolios under consideration. Generally, an accurate conditional volatility should be able to offer superior hedge effectiveness (*HE*) - Ku *et al.,* (2007). We calculate *HE* as *the variance reduction for a hedged portfolio compared with an unhedged portfolio*. Mathematically, the *HE* index can be computed as:

$$HE = \left[\frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \right] * 100 \qquad [2.5.3]$$

Table 2.8: Optimal portfolio weights, hedge effectiveness and ratios for Africa's equities and commodities

	MOROCCO	EGYPT	TUNISIA	SOUTH AFRICA	NAMIBIA	COTE D'IVOIRE	BOTSWANA
			Panel A: Stock-Oil Portfolio (Full sample period)				
Portfolio Optimal Weights (w^{so})	0.5182	0.5176	0.4979	0.5154			
Average OHR (γ^{so})	0.1162	0.0551	0.1566	0.2847			
Portfolio variances	2.0144	2.0170	1.9429	1.9931			
Hedge Effectiveness (%)	6.20	6.43	-0.73	4.26			
			Panel B: Stock-Gold Portfolio (Full sample period)				
Portfolio Optimal Weight (w^{sg})	0.5157	0.5143		0.5144			
Average OHR (γ^{sg})	0.1666	0.0418		0.4452			
Portfolio Variances	2.0260	2.0286		2.0050			
Hedge Effectiveness (%)	5.09	5.32		3.13			
			Panel C: Stock-Oil Portfolio (Sub-sample period)				
Portfolio Optimal Weight (w^{so})	0.5151	0.5093	0.4849	0.4939	0.4914	0.5376	0.4897
Average OHR (γ^{so})	0.1668	0.0865	0.1988	0.3709	0.2583	0.1502	0.1841
Portfolio Variances	2.1138	2.0964	2.0119	2.0451	2.0347	2.1999	2.0266
Hedge Effectiveness (%)	4.88	3.34	-4.99	-1.55	-2.61	**11.88**	-3.44
			Panel D: Stock-Gold Portfolio (Sub-sample period)				
Portfolio Optimal Weight (w^{sg})	0.5122		0.4832	0.4922	0.4893	0.6922	0.4875
Average OHR (γ^{sg})	0.1204		0.1728	0.2721	0.2298	0.1734	0.1776
Portfolio variances	2.1213		2.0195	2.0527	2.0422	2.2074	2.0342
Hedge Effectiveness (%)	4.18		-5.76	-2.30	-3.37	**11.24**	-4.20

Results are for both full sample (03/01/2003 to 29/12/2014) and sub-sample (15/09/2008 to 29/12/2014) periods. The table shows the average optimal weights of African stocks (w), hedge ratios (OHR) for stock-oil (γ^{so}) and stock-gold (γ^{sg}) portfolios, portfolio variances, as well as the hedge effectiveness of the portfolios. The abbreviations so and sg refer to stock-oil and stock-gold respectively.

where $Var_{unhedged}$ denote the variance of the unhedged portfolio's (African equities) returns; Var_{hedged} refers to the variance of the hedged portfolio's returns. The portfolio with the highest *HE* offers the best hedging strategy for constructing a stock-oil or stock-gold portfolio.

It can be observed from the HEs (Table 2.8) that all portfolios with optimal weights below 50% do not offer effective hedges (as their HEs are negative). For a portfolio with positive HE, the effectiveness of the hedges is low (with less than 15% HEs). Thus, even though realized optimal portfolio weights and hedge ratios indicate the need for a well-diversified stock-oil or stock-gold portfolio to include African stocks, the effectiveness of such hedging strategies may not be substantially active.

Despite this, international investors seeking to hedge their price risk in gold or crude oil markets with equities in Africa may have to look at the market in Cote d'Ivoire. The *HE*s of Cote d'Ivoire inclusive portfolio hedges are not only higher (11.88% and 11.24% for the stock-oil and stock-gold respectively) but also have relatively lower variance (risk) to *HE* ratios (in absolute terms) and possess the highest optimal portfolio weights.

2.4.5 Analysis of the hedging and diversification hypothesis

Although the conditional correlation results in Tables 2.6 and 2.7 provide useful information on the dynamic relations between the variables, it falls short at pointing out possible risk mitigating properties of African stocks in (extreme) unfavourable conditions of the commodities markets.[29] To be able to ascertain whether or not equities in Africa offer significant shield for losses in the commodity spot markets, we evaluate the hedge and diversification hypothesis developed by Baur and Lucey (2010) and present the results in Table 2.9. An asset with diversification feature does not assume negative or positive correlation on average but only takes a zero or negative correlation in specific periods. In this case, negative correlation in turbulent market conditions explains the asset's ability to compensate investors for their losses.

Table 2.9 depicts the hedge determining coefficient, d_0; diversification determining parameters, d_1, d_2, and d_3; and the total effects for extreme market behaviours, $Sum\ (d_1, d_2, d_3)$ for the different quantiles.

[29] Generally, correlations hold only on average and may be positive or negative in tranquil or crisis periods.

Estimates from the GARCH (1,1) model reveal high significance for the ARCH (α) and GARCH (β) parameters across board. Except for the regression estimates involving Cote d'Ivoire, South Africa, Botswana and Namibia, the degree of short-run persistence are very high (greater than 0.1) for all other markets. Estimates for South Africa, Nigeria, Mauritius, Kenya, and Tunisia are seen to have the highest long-run volatility persistence (with $\alpha + \beta$ close to unity). Analysis of the ARCH-LM test for lags 2 and 12 suggests that except for the model involving Mauritius, the presence of remaining ARCH effects is substantially minimized. In contrast to estimates from the DCC model, results from Table 2.9 indicate that no equity market in Africa provides hedge for any of the considered commodities.

This supports the opinion held by Baur and Lucey (2010) that an asset that offers hedge in normal periods may fail to exhibit similar characteristics in periods of market turbulence. The result is suggestive of the fact that global commodity investors react differently towards investments in Africa in periods of market calmness and crisis. A plausible explanation of this is that, saddled with significant losses and heightened uncertainty about their investments in international assets during extreme market meltdowns, international investors become doubtful about the prospects of emerging or developing markets to provide cushions for their losses. *Alternatively, they may prefer to shift their portfolios towards the relative safety of developed world markets.*

In spite of the African stocks' failure to offer hedging features for commodities during market turbulence, some provide considerable diversification characteristics. The diversification hypothesis is seen to be applicable for the following market pairs: Morocco-Platinum, Egypt-Cocoa, Egypt-Platinum, Tunisia-Cocoa, Tunisia-Silver, Kenya-Platinum, Kenya-S&P 500, Mauritius-Oil, South Africa-Cocoa, South Africa-Platinum, Botswana-Oil, Namibia-BCOM, Namibia-Oil, and Namibia-Gold.

Examining the above reveals that four markets (Morocco, Egypt, Kenya, and South Africa); three markets (Egypt, Tunisia, and South Africa); and two markets (Mauritius and Botswana) offer diversification properties for Platinum, Cocoa, and Oil respectively. In each set Egypt (for platinum), South Africa (Cocoa), and Botswana (for oil) are noted to offer the strongest diversifications since their parameters are more statistically different from zero. On account of the relatively stronger diversification characteristics of the above stock market-commodity pairs, we in turn proceed to evaluate the pairs in a diversified portfolio within the mean-variance framework. The implication of the stronger diversification properties for the above market pairs is that, investors who purchase African stocks during periods of crisis in the global commodity markets are compensated for loses from their global investments through positive returns.

2.4.6 Mean-variance portfolio selection and optimization with stocks in Africa

In this section, we examine within the mean variance portfolio optimization framework, the best portfolio combinations that will optimize returns whilst reducing variances. Particularly, we analyze varying portfolio mixes of stocks and commodities that produce the minimum variance without lowering returns. Figure 2.1 depicts the mean-variance portfolios for the first ten percentiles of portfolios that range from 0% (100%) in stocks (commodities) to 100% (0%) in stocks (commodities). The first panels of each set (A1, B1, and C1) show the risk and return of including African stocks in a stock-commodity portfolio without minimizing the variance. The second panels (A2, B2, and C2) show the set of all portfolios with economically meaningful risk-return trade-off (i.e. the efficient frontier). The upper blue lines in Panels A2, B2, and C2 indicate the efficient frontiers. Practically, the choice between any two portfolios on the efficient frontier requires trading a higher expected portfolio risk for a higher expected return.

A close observation from the plots shows that for a 100% investment in platinum, an international commodity investor could achieve a daily average return of 2.35% at a standard deviation of 1.42% (see Panel A1). However, by diversifying 61.60% into the Egyptian stock market, the investor could increase his daily expected portfolio returns to 5.86% whilst lowering the standard deviation to 1.23% (see Panel A2). Panel B1 reveals that a 100% investment in the cocoa spot market could earn an investor daily mean return of 1.23% with a risk component of 1.93%. Meanwhile, from the mean-variance standpoint, the daily mean return and risk probability could respectively be increased (decreased) from 2.77% (1.37%), with the inclusion of 46.88% of portfolio amount into the South African equity market (see Panel B2). Finally, within the mean-variance framework, including 11.29% of equities from Botswana is able to increase expected daily mean return from 1.72% to 1.85% whilst reducing portfolio standard deviation from 2.38% to 2.13% (see Panels C1 and C2).

Table 2.9: Results of hedge and diversification assessments using contemporaneous returns

	BCOM	COCOA	OIL	PLATINUM	SILVER	GOLD
MOROCCO						
d_0	-0.207	-0.231	0.057	0.144	-0.430	-0.716**
$d_1(q10)$	0.089	-0.004	0.026	0.076	0.147	0.032
$d_2(q5)$	0.105	-0.018	-0.022	0.111	0.134	0.221
$d_3(q1)$	0.365	0.659**	-0.245	**-0.636****	-0.233	-0.147
Sum (d_1, d_2, d_3)	0.559	0.637	-0.241	-0.449	0.048	0.106
α	0.135***	0.138***	0.136***	0.136***	0.134***	0.142***
β	0.809***	0.805***	0.809***	0.807***	0.813***	0.799***
ARCH-LM[2]	2.468[0.085]	2.426[0.089]	2.610[0.074]	2.335[0.097]	2.449[0.087]	2.334[0.097]
ARCH-LM[12]	1.145[0.319]	1.139[0.323]	1.181[0.290]	1.140[0.322]	1.144[0.319]	1.164[0.303]
EGYPT						
d_0	-0.697*	-0.048	1.149***	0.007	-0.376	-1.859***
$d_1(q10)$	0.086	0.486	0.091	0.112	-0.043	0.152
$d_2(q5)$	0.116	**-0.456****	0.392*	-0.101	-0.109	0.139
$d_3(q1)$	0.336	-0.089	-0.231	**-0.770***	0.303	0.714*
Sum (d_1, d_2, d_3)	0.538	-0.059	0.252	-0.759	0.151	1.005
α	0.111***	0.109***	0.131***	0.168***	0.120***	0.112***
β	0.827***	0.836***	0.438***	0.526***	0.803***	0.813***
ARCH-LM[2]	0.159[0.853]	0.188[0.829]	0.098[0.907]	0.272[0.762]	0.178[0.837]	0.292[0.747]
ARCH-LM[12]	1.320[0.199]	1.370[0.173]	3.081[0.000]	2.087[0.015]	1.091[0.363]	1.402[0.157]
TUNISIA						
d_0	-0.189	-0.046	0.292*	0.015	-0.071	-0.288*
$d_1(q10)$	-0.050	0.154**	-0.090	0.086	**-0.143****	-0.095
$d_2(q5)$	0.155*	**-0.152***	0.027	-0.069	0.145	0.014
$d_3(q1)$	-0.037	0.341**	-0.029	-0.108	-0.146	-0.068
Sum (d_1, d_2, d_3)	0.068	0.343	-0.092	-0.091	-0.144	-0.149
α	0.122***	0.122***	0.196***	0.193***	0.190***	0.184***
β	0.811***	0.811***	0.770***	0.773***	0.774***	0.781***
ARCH-LM[2]	4.323[0.013]	5.354[0.005]	0.136[0.873]	0.114[0.892]	0.176[0.839]	0.110[0.896]
ARCH-LM[12]	1.463[0.131]	1.689[0.063]	0.165[0.999]	0.169[0.999]	0.181[0.999]	0.178[0.999]

Table 2.9 continued.

	BCOM	COCOA	OIL	PLATINUM	SILVER	GOLD
KENYA						
d_0	-0.648**	-0.721***	0.820***	0.210	0.107	-0.803***
$d_1(q10)$	0.021	0.121	-0.096	0.021	0.152	-0.080
$d_2(q5)$	0.014	-0.197	0.270*	-0.197	-0.233	0.201
$d_3(q1)$	0.505**	0.833***	-0.310	**-0.747*** **	0.072	0.731***
Sum (d_1, d_2, d_3)	0.540	0.833	-0.136	-0.923	-0.009	0.852
α	0.199***	0.203***	0.196***	0.193***	0.190***	0.184***
β	0.762***	0.758***	0.770***	0.773***	0.774***	0.781***
ARCH-LM[2]	0.134[0.874]	0.118[0.889]	0.136[0.873]	0.114[0.892]	0.176[0.839]	0.110[0.896]
ARCH-LM[12]	0.159[0.999]	0.166[0.999]	0.165[0.999]	0.169[0.999]	0.181[0.999]	0.178[0.999]
GHANA						
d_0	-0.111	0.110	-0.314	0.144	0.023	-0.226
$d_1(q10)$	0.013	-0.035	0.108	-0.096	-0.071	0.138
$d_2(q5)$	-0.068	0.026	-0.184	0.223*	-0.054	-0.049
$d_3(q1)$	0.034	0.065	0.027	-0.077	-0.271	0.064
Sum (d_1, d_2, d_3)	-0.021	0.056	-0.049	0.060	-0.396	0.153
α	0.107***	0.113***	0.112***	0.115***	0.109***	0.113***
β	0.571***	0.568***	0.565***	0.563***	0.569***	0.564***
ARCH-LM[2]	0.243[0.784]	0.248[0.780]	0.255[0.775]	0.257[0.773]	0.251[0.778]	0.256[0.774]
ARCH-LM[12]	0.250[0.996]	0.241[0.996]	0.248[0.995]	0.248[0.996]	0.248[0.996]	0.248[0.996]
MAURITIUS						
d_0	-0.152	-0.244	0.001	-0.838***	-0.492**	-1.436***
$d_1(q10)$	0.093	0.050	**-0.231*** **	0.152*	-0.018	-0.048
$d_2(q5)$	-0.111	0.019	0.260**	-0.174	0.095	0.177*
$d_3(q1)$	0.173	-0.227	-0.135	0.718***	0.260	0.753***
Sum (d_1, d_2, d_3)	0.155	-0.158	-0.106	0.696	0.337	0.882
α	0.126***	0.125***	0.126***	0.129***	0.135***	0.124***
β	0.871***	0.872***	0.870***	0.869***	0.862***	0.872***
ARCH-LM[2]	15.858[0.000]	17.283[0.000]	16.253[0.000]	17.104[0.000]	16.027[0.000]	21.119[0.000]
ARCH-LM[12]	4.108[0.000]	4.345[0.000]	4.349[0.000]	4.353[0.000]	4.196[0.000]	5.315[0.000]

Table 2.9 continued.

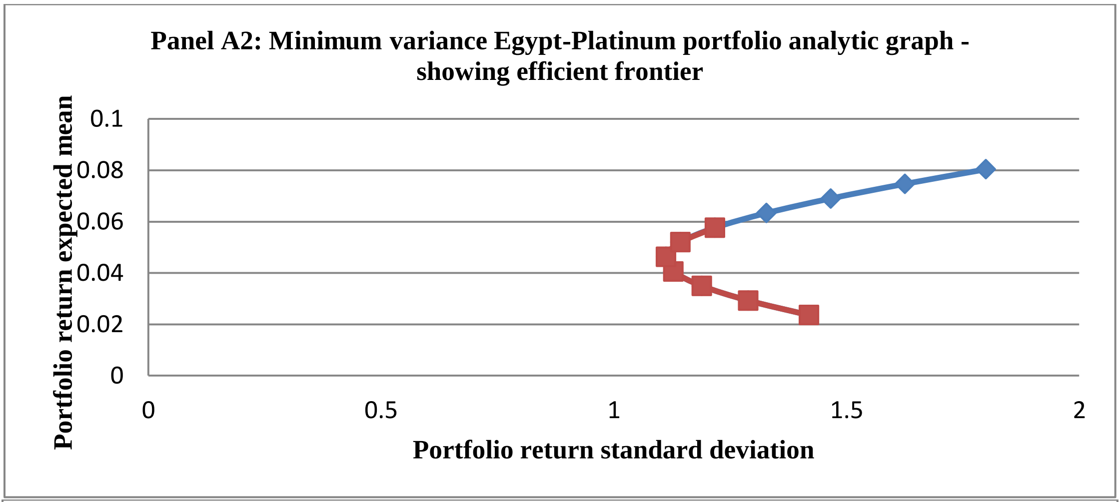
	BCOM	COCOA	OIL	PLATINUM	SILVER	GOLD
COTE D'IVOIRE						
d_0	-0.190	-0.143	-0.059	-0.381	-0.138	-0534
$d_1(q10)$	0.115	0.132	-0.031	0.028	0.055	-0.000
$d_2(q5)$	0.034	-0.159	0.010	0.393**	0.126	-0.060
$d_3(q1)$	0.226	-0.160	-0.197	0.167	-0.275	0.130
Sum (d_1, d_2, d_3)	0.375	-0.187	-0.218	0.588	-0.094	0.070
α	0.004***	0.006***	0.004***	0.005***	0.005***	0.004***
β	0.708***	0.895***	0.915***	0.919***	0.889***	0.927***
ARCH-LM[2]	0.704[0.495]	0.689[0.502]	0.664[0.515]	0.649[0.523]	0.652[0.521]	0.651[0.521]
ARCH-LM[12]	0.402[0.963]	0.351[0.979]	0.335[0.983]	0.338[0.982]	0.353[0.979]	0.337[0.983]
SOUTH AFRICA						
d_0	-0.020	0.274	0.455	0.072	-0.428	-1.056***
$d_1(q10)$	0.181	0.479***	-0.025	0.180	-0.149	0.210
$d_2(q5)$	0.114	**-0.756*** **	0.676***	0.123	0.539**	-0.203
$d_3(q1)$	0.006	0.153	-0.581	**-0.692***	-0.538	0.972***
Sum (d_1, d_2, d_3)	0.301	-0.124	0.070	-0.389	-0.148	0.979
α	0.066***	0.0666***	0.052***	0.066***	0.065***	0.070***
β	0.925***	0.925***	0.943***	0.926***	0.928***	0.923***
ARCH-LM[2]	0.355[0.701]	0.269[0.764]	2.704[0.067]	0.281[0.755]	0.550[0.577]	0.077[0.926]
ARCH-LM[12]	0.966[0.479]	0.897[0.550]	0.863[0.585]	0.960[0.485]	1.090[0.364]	0.810[0.641]
BOTSWANA						
d_0	-0.449**	-0.094	0.075	-0.335	-0.137	-0.683***
$d_1(q10)$	0.058	0.195**	0.105	0.230***	0.053	-0.083
$d_2(q5)$	0.120	-0.079	0.270**	-0.070	0.012	0.130
$d_3(q1)$	0.120	-0.103	**-0.366***	0.159	-0.206	0.464**
Sum (d_1, d_2, d_3)	0.291	0.013	0.009	0.319	-0.141	0.511
α	0.006***	0.004***	0.004***	0.005***	0.006***	0.005***
β	0.598**	0.678***	0.920***	0.597**	0.589**	0.590*
ARCH-LM[2]	0.124[0.883]	0.127[0.881]	0.138[0.871]	0.138[0.871]	0.124[0.884]	0.221[0.802]
ARCH-LM[12]	0.152[0.999]	0.139[0.999]	0.148[0.999]	0.152[1.000]	0.143[0.999]	0.241[0.996]

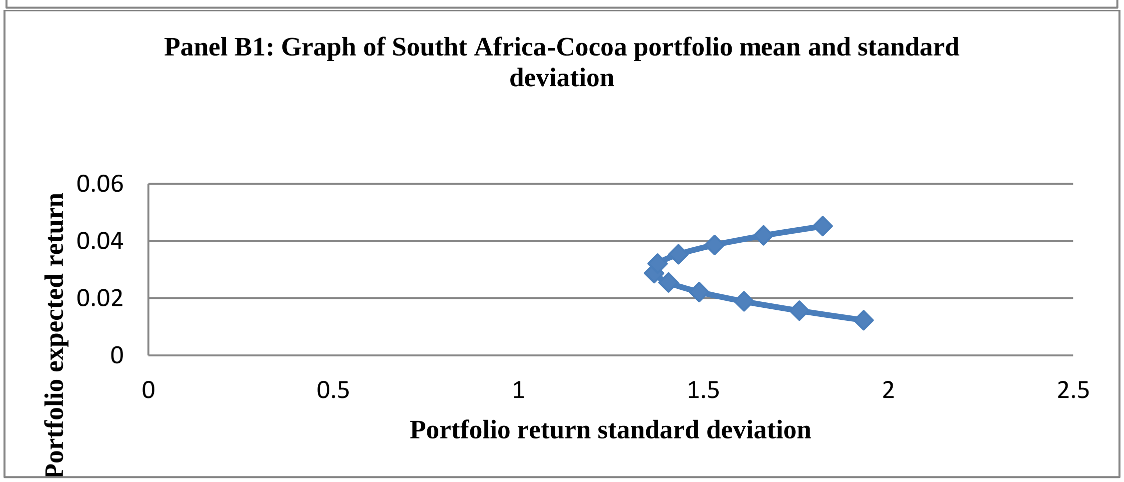
Table 2.9 continued.

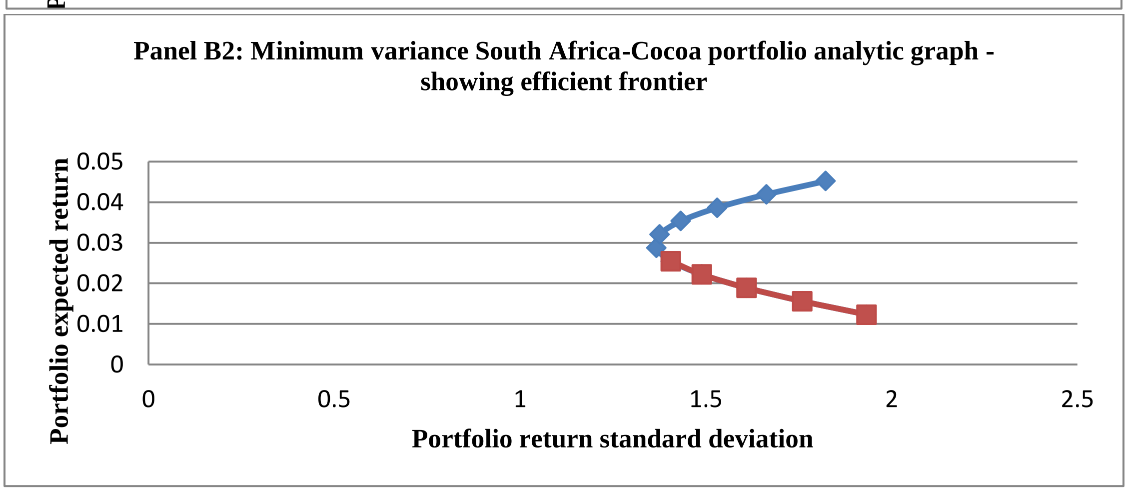
	BCOM	COCOA	OIL	PLATINUM	SILVER	GOLD
NIGERIA						
d_0	-0.827***	-1.125***	-1.414***	-1.349***	-0.316	-1.354***
$d_1(q10)$	-0.038	0.093	-0.063	-0.171	0.042	0.121
$d_2(q5)$	0.017	0.331*	0.365**	0.212	0.109	-0.111
$d_3(q1)$	0.412	-0.022	-0.190	1.066***	0.174	0.104
Sum (d_1, d_2, d_3)	0.391	0.402	0.112	1.107	0.325	0.114
α	0.292***	0.272***	0.290***	0.304***	0.297***	0.293***
β	0.664***	0.672***	0.662***	0.655***	0.661***	0.664***
ARCH-LM[2]	1.806[0.165]	2.301[0.100]	1.006[0.366]	1.508[0.222]	1.573[0.208]	1.404[0.246]
ARCH-LM[12]	1.723[0.056]	1.546[0.101]	1.768[0.048]	1.591[0.087]	1.636[0.075]	1.984[0.022]
NAMIBIA						
d_0	0.015	0.081	0.531*	0.003	-0.198	-0.423
$d_1(q10)$	0.045	0.139	-0.024	0.244**	-0.126	**-0.298*** **
$d_2(q5)$	0.316**	-0.094	0.499***	-0.188	0.245	0.260*
$d_3(q1)$	**-0.491***	-0.130	**-0.680** **	0.002	-0.157	0.670**
Sum (d_1, d_2, d_3)	-0.130	-0.085	-0.205	0.058	-0.038	0.632
α	0.282***	0.162***	0.038***	0.072***	0.064***	0.091***
β	0.421***	0.548***	0.696***	0.450***	0.522***	0.552***
ARCH-LM[2]	0.346[0.707]	0.320[0.726]	0.373[0.689]	0.399[0.671]	0.392[0.676]	0.392[0.676]
ARCH-LM[12]	0.340[0.982]	0.328[0.985]	0.381[0.971]	0.359[0.977]	0.345[0.981]	0.419[0.957]

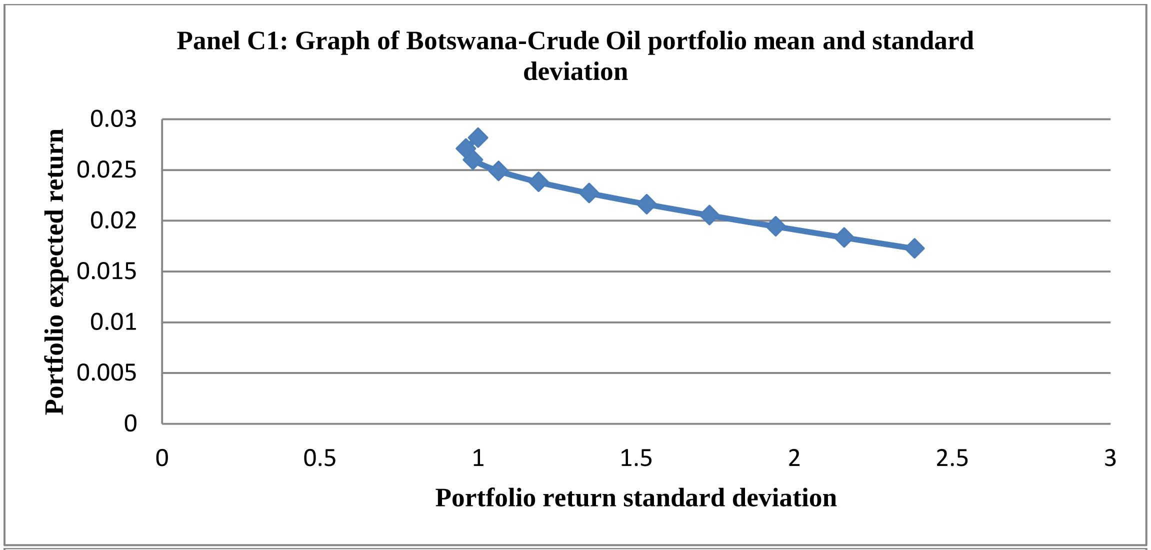
*The table shows results of a sample of 3,056 daily contemporaneous returns of African stocks, commodities and BCOM from 6 January, 2003 to 29 December, 2014 on a close-to-close basis. Columns 2-7 represent the regressors. Each equity market (in bold caps) in a row is a dependent variable. The coefficients d_0, d_1, d_2, d_3 are the parameters in eqn. 2.4.1. Zero d_0 suggest a weak hedge and negative d_0 accompanied by negative value of Sum (d_1, d_2, d_3) > d_0 (if negative) indicates that the stock is a strong hedge. Significantly zero (negative) d_1, d_2, and d_3 at q_1, q_5, and q_{10} (i.e. extreme market conditions) indicate that the associated equity market is a weak (strong) diversifier. α and β are the ARCH and GARCH parameter estimates from equation 2.4.2 indicating past shocks and volatility effects respectively. They are estimated using the Generalized Error distribution (GED) algorithm. ARCH-LM [2, 12] is the test for the presence of ARCH effects in the series at lags 2 and 12. The test statistic is distributed $\chi^2(\rho)$ under the null of no ARCH effects. Figures in bold denote safe-havens. ***, **,* denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.*

From the foregoing, it is clear that judging from the mean-variance point of view, adding African stocks to a diversified portfolio of stocks and commodities has the effect of lowering risk whiles simultaneously increasing expected returns. The performances of the three portfolio mixes thus show that Botswana offers a relatively meaningful average risk-return trade-off in the stock-oil portfolio at a relatively lesser cost.









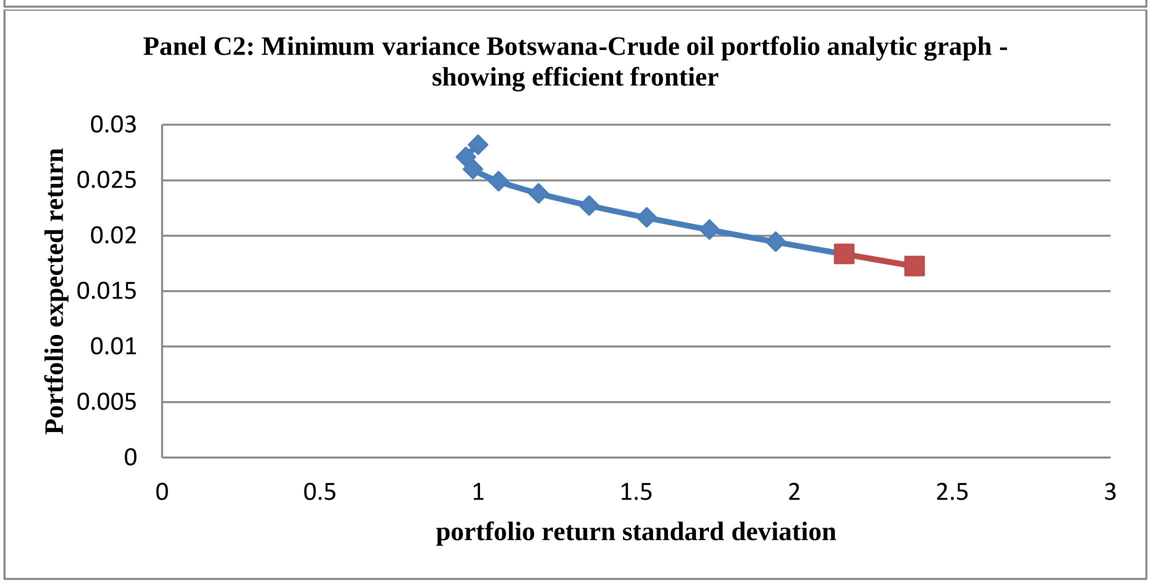


Fig. 2.1: Performances of African stocks-commodity portfolios mix from 3rd January, 2003 to 29th December, 2014. The graphs show the mean-variance portfolio optimization from the first ten percentiles of portfolios that range from 0% (100%) in stocks (commodities) to 100% (0%) in stocks (commodities). The upper blue lines in Panels A2, B2, and C2 indicate the efficient frontiers.

2.5 Conclusion

Owing to the increasing vulnerability of global markets to the effects of world economic meltdowns, investors have been on the look-out for alternative means to diversify their portfolios across diverse markets in order to escape losses during market turmoil. On account of the "decoupling" proposition that emerging markets' stock returns are not jointly normal with that of developed markets during crisis, it is anticipated that crashes in the world markets may not instantaneously affect returns from emerging markets making them sustainable hubs for diversification. This chapter examined the dynamic relationship between equity returns in Africa and returns on global markets with emphasis on the opportunities for diversification and risk reduction around the 2007-2009 global financial crisis. Particularly, the chapter explored the time-varying correlations and risk-return trade-off dynamics across Africa and the global markets.

The findings provide substantial evidence of time-varying lower correlations between African stocks and global markets influenced by the global financial crisis. Within the risk-return framework, though Egypt and South Africa show some minuscule signs of risk mitigating opportunities relative to the benchmark markets, their information ratios are highly anemic to internationally accepted thresholds. We further report evidence of time-varying slow changing conditional volatilities under the effects of return innovations for most African markets. It is recommended that international portfolio investors seeking to diversify across Africa should take into account volatility persistence, and present and past market conditions, as well as the stability of the considered markets. Additionally, we found evidence in support of the Forbes and Rigobon (2002) "shift-contagion" theory as against the decoupling phenomenon. The findings of the study may provide useful evidence to augment efforts of policy makers at promoting Africa as a hub for certain kinds of international investments.

References

African Development Bank (2013). Situational analysis of the reliability of economic statistics in Africa: special focus on GDP measurement. *African Development Bank*, Tunis.

African Securities Exchanges Association (2013). ASEA 2013 Year Book, available at: www. africansea.org/ASEA/Default.aspx.

Adu, G., Marbuah, G., Mensah, J. T. and Frimpong, P. B. (2013). Macro-economic development and stock market performance: A non-parametric approach. *Economics and Econometrics Research Institute Paper Series*, 1: 1-35.

Alagidede, P., (2008). African stock markets integration: Implications for portfolio diversification and international risk sharing. In the proceedings of the African Economics Conferences 2008, pp. 25-52. Available online at:
https://www.researchgate.net/profile/Paul_Alagidede/publication/265291275_African_Stock_Market_Integration_Implications_for_Portfolio_Diversification_and_International_Risk_Sharing/links/54ca82f70cf2c70ce5220162.pdf

Alagidede, P., (2010). Equity market integration in Africa. *African Review of Economics and Finance,* 1(2):88-119.

Aloui, C., Jammazi, R., (2009). The effects of crude oil shocks on stock market shifts behaviour: A regime switching approach. *Energy Economics*, 31:789-799; doi:10.1016/j.eneco.2009.03.009.

Anghelache, G-V., (2012). CAPM evaluating relation. *Revista Romana de Statistica-Supliment Trim* IV/2012, pp.147-154.

Ankrim, E.M. & Hensel, C.R., (1993). Commodities in asset allocation: A real-asset alternative to real estate. *Financial Analyst Journal*, 49(3):20-29.

Arouri, M., (2011). Does crude oil move stock markets in Europe? A sector investigation. *Economic Modeling*, 28:1716-1725.

Arouri, M., Nguyen, D., (2010). Oil prices, stock markets and portfolio investment: Evidence from sector analysis in Europe over the last decade. *Energy Policy*, 38:4528-4539.

Arouri, M.E.H, Lahiani, A., Nguyen, D-K., (2015). World gold prices and stock returns in China: Insights for hedging and diversification strategies. *Economic Modelling,* 42: 273-288.

Baur, D.G., Lucey, B.M., (2010). Is gold a hedge or safe haven? An analysis of stocks, bonds and gold. *The Financial Review*, 45:217-229.

Baur, D.G., McDermott, T.K., (2010). Is gold a safe haven? International evidence. *Journal of Banking and Finance,* 34:1886-1898; doi:10.1016/j.bankfin.2009.12.008.

Bastianin, A., Manera, M., (2014). How does stock market volatility react to oil shocks? *Energy Resources and Markets Series*, 1-26.

Beckmann, J., Berger, T., Czudaj, R., (2014). Does gold act as a hedge or safe haven for stocks? A smooth transition approach. *Economic Modeling*, 1-9; doi: dx.doi.org/10.1016/j.econmod.2014

Beckmann, J., Czudaj, R., (2013). Gold as an inflation hedge in a time-varying coefficient framework. *Ruhr Economic Papers*, No. 362; doi:dx.doi.org/10.4419/86788416.

Bernanke, B.S., (1983). Irreversibility, uncertainty, and cyclical investment. *Quarterly Journal of Economics*, 98:85-106.

Bessembinder, H., (1992). Systematic risk, hedging pressure, and risk premiums in future markets. *Review of Financial Studies*, 5: 637–667.

Bialkowski, J., Bohl, M.T., Stephan, P.M., Wisniewski, T.P., (2014). The gold price in times of crisis. *International Review of Financial Analysis*, 1-11; doi:dx.doi.org/j.irfa.2014.07.001

Blose, L.E., (2010). Gold prices, cost of carry, and expected inflation. *Journal of Economics and Business*, 62:35-47.

Boako, G., Omane-Adjepong, M., Frimpong, J.M., (2016). Stock returns and exchange rate nexus in Ghana: A Bayesian quantile regression approach. *South African Journal of Economics,* 84(1):149-179. doi: 10.1111/saje.12096.

Boako, G., Acheampong, I.A., Domeher, D., Frimpong, J.M., (2015). Economic forces and equity returns in Ghana: Symmetric dependence with quantile regression. *Ghanaian Journal of Economics, pp.86-108.*

Bodie, Z., Rosansky, V., (1980). Risk and returns in commodity futures. *Financial Analyst Journal*, pp. 27-39.

Brambila-Macias, J., Massa, I., (2010). The global financial crisis and Sub-Saharan Africa: The effects of showing private capital inflows on growth. *African Development Review*, 22:366-377.

Broner, F.A., Gelos, R.G., Reinhart, C.M., (2006). "When in peril, retrench: Testing the portfolio channel of contagion", *Journal of International Economics*, 69 (1): 203-30.

Brooks, C., Persand, G., (2001). Seasonality in Southeast Asian stock markets: Some new evidence on Day-of-the-Week effect. *Applied Economics Letters* 8: 155—8

Buyuksahin, B., Haigh, M.S., Robe, M.A., (2008). Commodities and equities: 'A market of one'? July 11, 2008). Available at SSRN: http://ssrn.com/abstract=1069862 or http://dx.doi.org/10.2139/ssrn.106986.

Buyuksahin, B., Robe, M., (2014). Speculators, commodities, and cross-market linkages. *Journal of International Money and Finance*, 42:38-70; doi:dx.doi.org/10.1016/jimonfin.2013.08.

Chang, E. C., Cheng, J.W., Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking and Finance*, 24:1651–1679.

Cheng, I-H., Xiong, W., (2013). Financialization of commodity markets. *The Annual Review of Financial Economics,* 6:419-41.

Cheng, I., Kirilenko, A., Xiong, W., (2012). Convective risk flows in commodity futures markets. NBER Working Paper No. 17921, March 2012, pp. 1-61.

Chevallier, J., Ielpo, F., (2014). Twenty years of jumps in commodity markets. *International Review of Applied Economics;* 28(1): 64-82.

CFTC (2008). Staff report on commodity swap dealers & index traders with commission recommendations, September 2008. CFTF Press Rel. # 5542-08, Sep. 11. http://www.cftc.gov/PressRoom/PressReleases/pr5542-08.

Choi, K., Hammoudeh, S., (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. *Energy Policy* 38 (8):4388–4399.

Ciner, C., Gurdgiev, C., Lucey, B. M. (2013) Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *International Review of Financial Analysis*, 29: 202 - 11.

Creti, A., Joets, M., Mignon, V., (2013). On the links between stock and commodity markets' volatility. *Energy Economics*, 37:16-28.

Daskalaki, C., Skiadopoulos, G., (2011). Should investors include commodities in their portfolio after all? New evidence. *Journal of Banking and Finance* 35:2606-2626.

Demirer, R., Lee, H-T., Lien, D., (2015). Does the stock market drive herd behaviour in commodity futures markets? *International Review of Financial Analysis*, 1-33; doi:10.1016/j.irfa.2015.006.

Driesprong, G., Jacobsen, B., Maat, B., (2008). Striking oil: Another puzzle? *Journal of Financial Economics,* 89:307-327.

Engle, R., (2002). Dynamic conditional correlation: A simple class of multivariate generalized Autoregressive conditional hetereoscedasticity models. *Journal of Business and Economic Statistics*, 20(3):339-350.

Forbes, K.J., Rigobon, J.R., (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance*, 57(5):2223-2261.

Frimpong, J. M. (2009). Economic forces and the stock market in a developing economy: Cointegration evidence from Ghana. *European Journal of Economics, Finance and Administrative Sciences*, 16: 128-140.

Gilbert, C.L., (2009). Commodity speculation and commodity investments. *Commodity Market Review, 2009-2010, pp. 1-189*. Available at http://www.fao.org/3/a-i1545e.pdf#page=39

Goodwin, T.H., (2009). The information ratio. In *Investment Performance Measurement: Evaluation and Presenting Results*. Edited by Philip Lawton and Todd Jankowski. Hoboken, NJ: John Wiley & Sons:705–718. Reprinted from *Financial Analysts Journal*, vol. 54, no. 4 (July/August 1998):34–43.

Gorton, G., Rouwenhorst, G.K., (2006). Facts and fantasies about commodity futures. *Financial Analysts Journal*, 6(2): 47-68.

Grinold, R.C., Kahn,. R.N. (1995). Active *portfolio management*. Chicago, IL.

Gupta, R., Modise, M.P., (2013). Does the source of oil price shocks matter for South African stock returns? A structural VAR approach. *Energy Economics,* 40:825-831.

Hamilton, J.D., (2009). Causes and consequences of the oil shock of 2007-2008. *Brookings Papers on Economic Activity*, Spring pp.215-261.

Hillier, D., Drapper, P., Faff, R., (2006). Do precious metals shine? An investment perspective. *Financial Analysts Journal*, 62:98-106.

Hong, H., Stein, J., (1999). A unified theory of under reaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54:2143-2184.

Hong, H., Torous, W., Valkanov, R., (2007). Do industries lead stock markets? *Journal of Financial Economics*, 83:367-396.

Hood, M., Malik, F., (2013). Is gold the best hedge and a safe haven under changing stock market volatility? *Review of Financial Economics*, 22:47-52; doi:dx.doi.org/10.1016/j.rfe.2013.03.001.

Harvey, C.R., (1991). In: Kodongo, O., Ojah, K., (2011). Foreign exchange risk pricing and equity market segmentation in Africa. *Journal of Banking and Finance*, 35:2295-2310.

Huang, Y., Guo, F. (2008) Macro shocks and the Japanese stock market. *Applied Financial Economics*, 18:1391–400. doi:10.1080/09603100701720393

Jahan-Parvar, M., Vivian, A., Wohar, M.E., (2012). Predictability and under reaction in industry-level returns: Evidence from commodity markets. SSRN working paper http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2005365.

Jones, C., Kaul, G., (1996). Oil and the stock market. *Journal of Finance*, 51:463-491.

Kanas, A. (2000). Volatility spillovers between stock returns and exchange rate change international evidence. *Journal of Business Finance and Accounting*, 27(3): 447-466.

Kasekende, L., Ndikumana, L., Taoufik, R., (2009). Impact of the global financial and economic crisis on Africa. *African Development Bank Working Paper Series*, 96.

Keith, C., Nitzsche, D., (2005). Quantitative financial economics: stocks, bonds & foreign exchange. *John Wiley & Sons Ltd England*; ISBN:978-0-470-0917-1-5, pp. 169-203.

Keynes, J.M., (1923). Some aspects of commodity markets. *Manchester Guardian Commercial, European Reconstruction Series, Section* 13, 784-786.

Kidd, D., (2011). Sharpe ratio and the Information ratio. *Investment Performance Measures – CFA Institute,* pp.1-4.

Kilian, L., (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3):1053-1069.

Kodongo, O., Ojah, K., (2011). Foreign exchange risk pricing and equity market segmentation in Africa. *Journal of Banking and Finance*, 35:2295-2310.

Kroner, K.F., Ng, V.K., (1998). Modeling asymmetric movements of asset prices. *Review of Financial Studies*, 11:844-871.

Krugman, P., (2008). Fuels on the hill. *The New York Times* (June 27).

Ku, Y. -H., Chen, H. -C., Chen, K. -H. (2007). On the application of the dynamic conditional correlation model in the estimation of optimal time-varying hedge ratios. *Applied Economic Letters*, 14:503–509.

Kyle, A.S., Xiong, W., (2001). Contagion as a wealth effect. *Journal of Finance*, 56(4):1401-1440.

Lee, K., Ni, S. (2002). On the dynamic effects of oil price shocks: A study using industry level data. *Journal of Monetary Economics, 49*:823–52.doi: 10.1016/S0304-3932(02)00114-9

Lean, H.H., Nguyen, D.C., (2014). Policy uncertainty and performance characteristics of sustainable investments across regions around the global financial crisis. *Applied Financial Economics*, 24(21):1367-1373; doi: dx.doi.org/10.1080/09603107.2014.925063.

McCown, J.R., Zimmermann, J.R., (2006). Is gold a zero-beta asset? Analysis of the investment potential of precious metals. Available at SSRN: http://dx.doi.org/10.2139

Mensi, W., Hammoudeh, S., Reboredo, C.J., Nguyen, D.K., (2014). Do global factors impact BRICS stock markets: A quantile regression approach. *Emerging Markets Review*, 19:1-17; doi:dx.doi.org/10.1016/j.emermarr.2014.04.002.

Moin, S., (2007). New frontier markets tempt investors. *African Review of Business and Technology,* 1:1-7.

Moss, T.J., Thuotte, R., (2013). No where to hide? Stock market correlation, regional diversification, and the case for investing in Africa. *Center for Global Development Working Paper* No. 316, pp.1-20.

Moss, T.J., Ramachandran, V., Standley, S., (2005). Why doesn't Africa get more equity investment? Frontier markets, firm size and asset allocations of global emerging equity funds. *Centre for Global Development Working Paper*, 112.

Nayaran, P.K., Sharma, S.S., (2011). New Evidence on oil price and firm returns. *Journal of Banking and Finance*, 35(12):3253-3262.

Ntim, C.G., (2012). Why African stock markets should formally harmonize and integrate their operations. *African Review of Economics and Finance*, 4 (1): 53-72.

Ntim, C.G., Oppong, K.K., Danbolt, J., Dewotor, F., (2011). Testing the weak-form efficiency in African stock markets. *Managerial Finance*, 37(3): 195-218.

Odusami, B. O. (2009). Crude oil shocks and stock market returns. *Applied Financial Economics*, 19, 291–303. doi:10.1080/09603100802314476

Olson, E., Vivian, A.J., Wohar, M.E., (2014). The relationship between energy and equity markets: Evidence from volatility impulse response functions. *Energy Economics*, 43:297-305.

Park, J., Ratti, R.A., (2008). Oil price shocks and stock markets in the U.S. and 13 European countries. *Energy Economics*, 30:2587-2608; doi:10.1016/j.eneco.2008.04.003.

Pasutasarayut, P., Chintrakarn, P., (2012). Is gold a hedge or safe haven? A case study of Thailand. *European Journal of Science Resources,* 74:90-95.

Pesaran, B., Pesaran, M.H., (2009). Time series econometrics using Microfit 5.0. *Oxford University Press,* pp. 237-248.

Phan, D.H.B., Sharma, S.S., Narayan, P.K., (2015). Oil price and stock returns of consumers and producers of crude oil. *Journal of International Financial Markets, Institutions & Money*, 34:245-262; doi: dx.doi.org/10.1016/j.intfin.2014.010.

Pindyck, R., (1991). Irreversibility, uncertainty and investment. *Journal of Economic Literature*, 29(3):1110-1148.

Pukthuanthong, K., Roll, R., (2009). Global market integration: an alternative measure and its application. *Journal of Financial Economics*, 94: 214-232.

Rafailidis, P., Katrakilidis, C., (2014). The relationship between oil prices and stock prices: A nonlinear asymmetric cointegration approach. *Applied Financial Economics*, 24:793–800. doi:10.1080/09603107.2014.907476

Senbet, L., Otchere, I., (2008). Beyond Banking: Developing markets-African stock markets. IMF Seminar, Tunisia.

Silvennoinen, A., Thorp, S., (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets Institutions & Money*, 24(1):42-65.

Simatele, M., (2014). Reflections on the impact of the financial crisis on sub-Saharan Africa. *Africa Growth Agenda*, 18-24.

Singleton, K., (2012). Investor flows and the 2008 boom/bust in oil prices. *Management Science*, pp.308-318..

Smith, G., Jefferis, K., Ryoo, H.-J., (2002). African stock markets: Multiple variance ratio tests of random walks. *Applied Financial Economics*, 12:475-84.

Sockin, M., Xiong, W., (2012). Informational frictions and commodity markets. *The Journal of Finance,* 70 (5): 2063-2098.

Tang, K., Xiong, W., (2012). Index investment and financialization of commodities. *Financial Analysts Journal* 68 (6), 54-74.

Teo, M., (2009). "The geography of hedge funds. *Review of Financial Studies*, 22 (9):3531-61.

Tully, E., Lucey, B.M., (2007). A power GARCH examination of the gold market. *Research in International Business and Finance,* 21:316-325.

UNDP (2003). African stock markets handbook, United Nations Development Programme, New York, NY.

Vo, M., (2011). Oil and stock market volatility: A multivariate stochastic volatility perspective. *Energy Economics*, 33:956-965.

Vivian, A., Wohar, M.E., (2012). Commodity volatility breaks. *Journal of International Financial Markets Institutions and Money* 22 (2), 395–422.

Wei, C. (2003). Energy, the stock market, and the putty-clay investment model. *American Economic Review,* 93:311-323.

Worthington, A.C., Pahlavani, M., (2007). Gold investment as an inflationary hedge: Cointegration evidence with allowance for endogenous structural breaks. *Applied Financial Economics*, 3:259-262.

Xu, B., (2015). Oil prices and UK industry-level stock returns. *Applied Economics*, 47(25): 2608-2627.

Yang, L., Garcia, P., (2014). Portfolio investment: Are commodities useful? Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, M.O. pp.138.

You, L., Daigler, R., (2013). A Markowitz optimization of commodity futures portfolios. *Journal of Futures Markets,* 33(4):343-368.

Zagaglia, P., Morzo, M., (2013). Gold and the U.S dollar: Tales from the turmoil. *Quantitative Finance, 13:571-582.*

Appendix 2A:

Heteroscedasticity and autocorrelation tests results

Diagnostics	**TUN**	**SA**	**NIG**	**NAM**	**MOR**	**MAU**	**BOT**	**EGY**	**COT**
LBQ[12]	0.000	0.001	0.000	0.522	0.000	0.000	0.882	0.000	0.843
LBQ^2[12]	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.986
ARCH[12]	0.000	0.000	0.000	1.000	0.000	0.000	**0.999**	0.000	**0.985**
	GHA	**KEN**	**BCOM**	**COC**	**GOL**	**OIL**	**PLT**	**SIL**	
LBQ[12]	0.000	0.000	0.087	0.002	0.000	0.000	0.012	0.934	
LBQ^2[12]	0.377	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
ARCH[12]	**0.387**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Notes: *shows test of autoregressive conditional heteroscedasticity (ARCH) and Ljung-Box test for autocorrelation for the series (LBQ) and squared series (LBQ^2) for 12 lags. The series is made up of Tunisia (TUN), South Africa (SA), Nigeria (NIG), Namibia (NAM), Morocco (MOR), Mauritius (MAU), Botswana (BOT), Egypt (EGY), Cote D'Ivoire (COT), Ghana (GHA), Kenya (KEN), Bloomberg Commodity Index (BCOM), Cocoa (COC), Gold (GOL), OIL, Platinum (PLT), and Silver (SIL).*

CHAPTER THREE

Co-Movement of Africa's Equity Markets: Regional and Global Analysis in the Frequency-Time Domains

3. Introduction

Among other factors, with an anticipated human population growth of about 1.458 billion by 2025 – see the World Bank factsheet on population estimates[30], Africa is increasingly becoming a frontier for investment and world economic development.[31] Increases in demographic transitions opens a window of opportunities, as the working age population increases. This presents opportunity to open up the African market to enhance intra-African trade, as well as the flow of capital across borders and between Africa and the rest of the world over time. Recent trends in African total trade flows – exports and imports, highlight a shift in trade dynamics and increasing competition from China for the African market (AfDB, OECD, UNDP, 2015). From 2010 to 2013, intra-African exports grew by 50% and by another 11.5% in 2014 to USD61.4 billion. Despite Europe's dominance in African trade, Africa's trade with Asia rose by 22% between 2012 and 2013. Moreover, since 2000 official remittances to Africa increased six-fold and were projected to reach USD64.6 billion in 2015 with Egypt and Nigeria receiving the bulk of flows. At the same time, increasing Greenfield investments from China, India, and South Africa are expected to increase foreign investment in the continent. The resultant effects of these are improvements in the overall economic growth and developments in the financial sector. In fact, Ahmed *et al.,* (2014) estimates the contribution of Africa's demographic dividend to gross GDP volume growth of 10-15% by 2030.[32] Standard economic theory postulates that the flow of foreign capital to a recipient country increases its stock of capital and technological knowledge, leading to better economic performance. Capital flows could also provide additional capital to local savings, promote capital accumulation, and market efficiency.

To reap the above benefits, African countries ought to establish stronger ties and collaborations with the global economy. However, the degree and extent of both inter- and intra-regional interconnectedness ought to be pegged at certain optimal levels in order to reap benefits from scale

[30] https://africacheck.org/factsheets/factsheet-africas-population-projections/

[31] Bodenhorn and Cuberes (2010) establish positive correlation between financial development and city growth robust to controls for city geographical characteristics, percentage of population working in different sectors, and initial population of a city.

[32] Unless otherwise stated, figures are gleaned from AfDB, OECD, UNDP (2015) African Economic Outlook report.

economies.[33] In the past three decades, efforts at integrating Africa regionally and globally have been aggressively pursued, albeit with some challenges. For instance, Africa has managed to significantly attain progress in economic integration including progressive development of regional infrastructure and removal of some barriers to intra-regional trade (Mougani, 2014). Despite this, progress in economic convergence, as well as, monetary coordination and financial sector integration remains slothful (Mougani, 2014). At the same time, lessons from the Eurozone suggest that efforts at attaining economic convergence can better be enhanced on the wheels of prior monetary coordination and sufficient levels of financial integration, regionally and globally. In African Development Bank's (AfDB) 2014 policy paper on the continent's Regional Integration, Litse and Mupotola (2014) recommend that the Eurozone model of economic convergence should incite African Regional Economic Communities (RECs) to adopt measured and thoughtful approaches towards integration by meeting some basic conditions including financial sector integration.

The call to ensure stronger ties of the African financial sector regionally and globally has attracted various scholars to empirically examine the level and extent of co-movements and integration of African financial markets. In Africa, among the studies that have investigated the linkages between domestic and/regional and global financial markets, as well as various economic variables are Pukthuanthong and Roll (2009), Alagidede (2010), Ntim (2012), Moss and Thuotte (2013), Chinzara and Kambadza (2014), Motelle and Biekpe (2015), etc. These studies highlight the avenues for economic development, risk reduction, markets efficiency and enhancement, portfolio diversification, and financial stability.[34] Whilst the above studies make significant contribution to the literature on African financial markets inter-linkages with the rest of the world, their contribution to exploring regional dynamics in stock markets co-movements, as well as drawing useful and practical inferences for short-term and long-term investors appears lacking. Thus, this chapter fills the gap with more flexible and localized co-movements analysis. The method employed also allows for an assessment of the impact of investment horizon. From the point of view of portfolio diversification, short-term or long-term investors are more concerned with co-movements at higher or lower frequencies to help them formulate investments strategies. Thus, we are able to make a distinction between the short-term and long term investor, as well as their investments horizons.

[33] Though highly integrated markets may present fertile grounds for shock spillover the benefits of integration cannot be overemphasized. An aggressive pursuit of integration will not only help in risk diversification but also help smooth the impact of shocks – Beck et al., (2009).
[34] It is important to stress that results from these studies are not uniform.

Despite considerable efforts by extant studies to examine the nature and/level of African stock markets' co-movement, some significant gaps still exist to warrant further research attention. First, estimation methods adopted by the cited references fail to capture co-movement within the frequency-time spectrum capable of aiding in the formulation of investment strategies that take into account the needs of the short-term and long-term investor. Second, it is not clear at the moment, the nature of regional co-movements of African stock markets. Third, the role played by the 2007-2009 global financial crisis (GFC) in moderating regional and global co-movements of equity markets in Africa has not been profoundly investigated. Meanwhile, such development is likely to affect the level of cross-border listings of stocks and liquidity in the financial system with consequential effects on co-movements. On the basis of the above, this chapter examines African stock markets co-movement, regionally and globally over time. Particularly, the results are expected to identify the regional or global market that has the strongest linkages with markets in Africa, and the nature of the linkages. Additionally, the periodicity of the market nexus is investigated to account for the presence of any significant and/or persistent business/market cycles characterizing the intensity of cross-market co-movements. Such analyses may have useful implications for hedging and diversification strategies of investors, as well as for policy makers in surmounting the conundrums of Africa's financial markets integration agenda and shaping policy responses towards coordinated and independent financial markets.

The chapter contributes to the existing literature in different perspectives. First, converse to studies that analyze co-movement within one asset market, we are keen in investigating whether co-movement exists within same and among different asset classes. Thus, we examine co-movements of: (i) related regional or global stock markets (thus market-to-market co-movement), (ii) stock and commodities markets (market-to-commodities co-movement), (iii) stocks and currency markets (markets-to-currency price co-movement). The concept of commodity 'financialization'[35] underscores the need for the inclusion of commodities in a diversified portfolio with stocks since commodities show equity-like returns and low correlation with traditional assets (Gorton and Rouwenhorst, 2006). Additionally, since currency price changes interact with stock prices through either the portfolio balance theory or international trade/flow oriented model, examining the dynamic nexus between currencies and stock returns is very useful for fund managers and market

[35] The process of speculative market participants' consideration of commodities as investment assets is referred to as the "financialization" of commodities.

participants. In fact, Bekaert and Harvey (2014) recommend for the inclusion of new sub-segments such as currencies and bonds in related studies. With the inclusion of such new sub-segments, it is expected that co-movement may be detected even when the equity markets of two economic blocks are not directly linked together. The challenge associated with the approach by previous studies is that, the scope for co-movement becomes limited for both diversified and undiversified markets. Thus, we argue that the reliance on only stock markets' data-sets to model co-movement may be necessary but not sufficient condition.

Second, in contrast to earlier studies in Africa (for example, Alagidede, 2010; Moss and Thuotte (2013), Chinzara and Kambadza (2014), etc.), we examine co-movement of equity markets volatilities (see similar approaches in, Nikkinen *et al.,* 2006; and Garham and Nikkinen, 2011). The rationale is that volatility quantifies the risk of a stock market, and therefore, it is relevant to portfolio managers when rebalancing their portfolios from one market to another (Garham and Nikkinen, 2011). This logic is more grounded following the advent of the 2007-2009 global financial crisis (GFC) that heightened market uncertainties and price fluctuations. Reaction of market participants differ in periods of high and low market volatilities affecting the overall informational flow, cross-market listings, markets microstructures, and the degree and nature of co-movements. The results therefore may provide risk managers and policy makers with deeper comprehension of equity markets dynamics across geographical regions, thus helping them in devising effective hedging strategies. This makes our results robust to existing ones on African markets co-movements.

Methodologically, we employ the wavelet estimation technique (which, to the best of our knowledge has not seen substantial application in this area of research, particularly, on Africa stock markets). This constitutes a significant advancement in the empirical studies on emerging equity markets co-movements. Earlier and recent studies worldwide, have predominantly used cross-market correlation analysis (e.g. Longin and Solnik, 1995), various ARCH and GARCH models (e.g. Carrieri, *et al.,* 2007), and standard Granger causality or cointegration analysis (e.g. Voronkova, 2004; Alagidede, 2010) as the metrics for estimating co-movements of equity markets. However, these methods mostly fail to account for time-variations in co-movements, as well as their frequency-time domain analysis. Meanwhile, an understanding of the frequency-time domain co-movements helps in the assessment of the impact of investment horizons. Among the class of models noted to have strengths in overcoming the above shortfalls in contemporary literature are wavelet techniques (see for example, Garham and Nikkinen, 2011; Madaleno and Pinho, 2012; Chakrabarty *et al.,* 2015; Chang and Lee, 2015, etc.). The wavelet analysis helps in the localization in frequency and time domains; has the ability to breakdown any ex-post variables on different frequencies to examine the subtleties of joint movements across diverse time horizons without losses in information; and also provides a better trade-off between detecting oscillations and peaks or discontinuities. The method also simultaneously allows for an assessment of the impact of investment horizon. From the point of view of portfolio diversification, short-term or long-term investors are more concerned with the co-movements at higher or lower frequencies to help them formulate their investments strategies. Thus, through wavelets we are able to make a distinction between the short-term and long term investor, as well as their investments horizons.

3.1 Research design

3.1.1 The continuous Morlet wavelet transforms

Basically, wavelet transforms are of two categories: the continuous wavelet transforms (CWT) and the discrete wavelet transforms (DWT). Whereas the CWT is useful for extracting features, the DWT is mainly used for noise reduction and data compression (Madaleno and Pinho, 2012). Analyses of co-movements in this chapter are done with the CWT with the package (WaveletComp) developed by Roesch and Schmidbauer (2014) – see reference for details of the package and its functionality. The Morlet wavelet allows for good identification and isolation of periodic signals, by providing a balance between localization of time and frequency (Grinstead *et al.,* 2004), and also provides a better trade-off between detecting oscillations and peaks or discontinuities. The Morlet wavelet, a plane wave modulated by Gaussian can be expressed in the simplest form as:

$$\varphi(\eta) = \pi^{-\frac{1}{4}} e^{i\eta\psi} e^{-\frac{\eta^2}{2}}, \qquad [3.0]$$

where, η is non-dimensional 'time' parameter. The "angular frequency" ψ (or rotation rate in radians per unit time) is set to 6 to generate the admissibility of the Morlet function. The period or inverse frequency measured in time units is equal to $2\pi/6$, since one revolution equals 2π (radians). $\varphi(\eta)$ is complex, nonorthogonal, and normalized to have unit energy.

For proper examination of the time-varying relationship between two time series, we apply the bivariate concept called the wavelet coherence. A better definition of the wavelet coherence can be attained by considering the cross-wavelet transform and wavelet power spectrum and phase difference. The concept of cross-wavelet analysis provides appropriate tools for (i) comparing the frequency contents of two time series, (ii) deriving conclusions about the synchronicity of the series at specific periods and across certain ranges of time – see Roesch and Schmidbauer (2014). The cross-wavelet transform is able to decompose the Fourier co- and quadrature-spectra in the frequency-time domain. Defined by Torrence and Compo (1998), the cross-wavelet transform (XWT) of two time series x_t and y_t can be specified as: $W^{xy} = W^{x}W^{y*}$; where W^{x} and W^{y} are the wavelet transforms of x and y, respectively, and * denotes a complex conjugate. WaveletComp implements the rectified version given as:

$$W^{xy}(s,\tau) = \frac{1}{\tau}.W^{x}(s,\tau).W^{y*}(s,\tau) \qquad [3.1]$$

where s and τ respectively refer to frequency and time. The modulus of equation [3.1] can be construed as cross-wavelet power – assessing the similarity of the two series' wavelet power in the frequency-time domains (Roesch and Schmidbauer, 2014). It also shows the areas in the time-frequency space where the time series depicts a high common power, i.e. it denotes the local covariance between the time series at each scale (Vacha and Barunik, 2012). The cross wavelet power (*P*) is given as:

$$P^{xy}(s,\tau) = |W^{xy}(s,\tau)| \qquad [3.2]$$

Similarly, in a univariate framework, the power spectrum of each wavelet transform can be taken as the modulus of that wavelet transform. Thus the power spectrum of x is $|W^{x}|^{2}$. It depicts the distribution of the energy (spectral density) and local variance of a time series across the two-dimensional frequency-time space leading to a frequency-time representation (see also Torrence and Compo, 1998; and Madaleno and Pinho, 2012; for deatails).

The phase for wavelet depicts any lead/lag linkages between two time series, and can be defined as:

$$\theta_{xy} = \tan^{-1}\frac{I\{W_t^{xy}\}}{\Re\{W_t^{xy}\}}, \qquad \theta_{xy} \in [-\pi, \pi] \qquad [3.3]$$

An absolute value of θ_{xy} less (larger) than $\pi/2$ indicates that the two series move in phase (anti-phase, respectively) referring to the instantaneous time as time origin and at the frequency under consideration, while the sign of the phase shows which series is the leading one in the relationship. In the graphical plots, the phase vectors are shown by arrows.

Similar to Fourier coherency which measures the cross-correlation between two time series as a function of frequency, wavelet coherency is also considered as the equivalence of correlation coefficient, though there are significant differences between them (see Madaleno and Pinho, 2010, pp. 12). Wavelet coherency requires smoothing of both the cross-wavelet spectrum and the normalizing individual power spectra. In line with Torrence and Webster (1999), we define the wavelet coherence of two time series *x* and *y* as:

$$R_t^2(s) = \frac{|S(s^{-1}W_t^{xy}(s))|^2}{S(s^{-1}|W_t^x(s)|^2).S(s^{-1}|W_t^y(s)|^2)} \qquad [3.4]$$

where *S* is a smoothing operator. It can be noticed that the definition in equation [3.4] mimics the traditional correlation coefficient, and it is useful to think of the wavelet coherence as a localized correlation coefficient in the frequency-time space (Madaleno and Pinho, 2010; Tiwari *et al.,* 2014). Wavelet coherence near one shows a higher similarity between the time series, whilst coherence near zero depict no relationship.

3.2 Data and baseline analysis

Analysis in the chapter cut across different market classifications namely: African (frontier),[36] developed, emerging, foreign exchange, and commodities. Data are of daily periodicity and span the period 3rd January 2003 to 29th December, 2014. All data are gleaned from DataStream except the commodities market index which is sourced from Bloomberg. To avoid the effects of non-synchronous trading, the close-to-close method is used to eliminate data points that fall on non-trading or holidays of other markets. All series in the study are analyzed in their volatilities (based on absolute returns computed as the log difference between daily prices or indices). Specifically, the data consist of Morgan Stanley Capital International (MSCI) stock indices of eight largest African markets: Ghana, Nigeria, South Africa, Botswana, Morocco, Tunisia, Egypt, and Kenya. Additionally, prices of MSCI world index, which is comprised of developed world markets (hereafter referred to as MSCI developed markets index: (MSCI-DW)), MSCI emerging markets (MSCI-EM)

[36] The following African markets of our sample have the following classifications: South Africa, Egypt, and Nigeria are considered as emerging markets by the IFC (1999) classification. Additionally, Kenya, Morocco (MSCI classification as frontier markets); and currently Ghana and Botswana are being considered as frontier markets by MSCI (Berger et al., 2011).

index, Bloomberg Commodities (BCOM) index, and bilateral exchange rates between individual African countries on one hand, and each of the euro and US dollar, on the other hand, are included in the sample. All indices/prices are expressed in U.S dollars, excluding the bilateral exchange rates with the euro. The use of common currency returns in related studies has been justified to be most appropriate in alleviating exchange rate noise (Pukthuanthhong and Roll, 2009).

To examine regional co-movements, all African equity markets with available and reliable data are aggregated into four regions: East Africa, West Africa, Southern Africa, and North Africa. The aggregation is useful due to the structural differences and non-homogeneous nature of regional economic/financial development in Africa, despite significant similarities. Again, Development characteristics of equity markets in Africa are not the same across regions on the continent - see Alagidede, (2008) and Ntim *et al.,* (2011) for details of financial markets development in Africa. The aggregation is also to help academics and investors understand better how financial markets development in one region is closely linked with developments in individual domestic markets across the continent. This will provide useful insights on the levels of regional equity market harmonization in Africa.

Regional stock prices/indices (computed as market or value-weighted average prices) are therefore constructed from individual market indices with useful and reliable available data based on a specific geographic distribution. Including a stock from a given market in the regional index may result in upward bias or idiosyncratic market shocks in the regional index. For this reason, the valued-weighted regional index used for the bivariate estimations with each individual African market *i*, excludes that market, ostensibly to focus on shocks that are external to each market. Formally, the regional market valued-weighted index/price (p_t) excluding each individual market *i*, is computed as:

$$p_t = \sum_{t=1}^{T-i} w_{t,j} DPI_{t,j}^{q} \qquad [3.5]$$

where, *q* denotes any other market in the region, except *i*; $DPI_{t,j}^{q}$ is the daily price/index of market *q* in region *j*; w_t is the weight (which denotes the market capitalization) of each *q*, and *T* = total number of markets in a region. w_t is expressed as a fraction of the total market capitalization of all markets in the region. Because market capitalizations are of lower frequencies than daily indices, we use recently available end of year market capitalizations. For countries without current market capitalization observation, the most recently available one is used (consistent with Berger *et al.,* 2011). All market capitalizations data are sourced from World Development Indicators, 2015 CD-ROM, and the websites of the African Securities Exchanges Association (ASEA) and individual country specific stock exchanges.

Tables 3.0A and 3.0B present descriptive statistics of returns (volatility) of all markets and each bilateral exchange rate, respectively. In Table 3.0A, it is observed that the volatility returns of all individual African markets, as well as regional and global counterparts posted positive mean values during the sample period. The highest (lowest) mean values of 0.01275 (0.00075) are seen with South Africa (North Africa). All sample series have positive skewness and exhibit leptokurtic innovations. The Egypt and East African stock markets possessed the highest and lowest standard deviations respectively. In Table 3.0B, we note that the highest (lowest) daily mean volatilities of 0.0080 (0.0011) are recorded by the South African rand/dollar and the Egyptian pounds/dollar exchange rates. Similar to Table 3.0A, the volatilities of all exchange rates are positively skewed and highly peaked. We identify the Botswana pula/dollar and South African rand/dollar on one hand, and the Moroccan dirham/euro rates to have respectively the highest and lowest standard deviations.

As a prelude to our examination of co-movements, we examine time plots and follow the work of Zeiles *et al.,* (2003) to investigate the presence of multiple structural breaks/changes of the series, ostensibly to detect common stochastic trends – see also Garham and Nikkinen (2011) and Lee (2004). Figure 3.0 shows plots of variances of all considered series over the entire span of the data. Since volatilities are based on absolute returns, it is assumed that until certain unexpected changes (probably arising from new information) occurs; the series will continue to exhibit unconditional mean-reversion behaviour in their variances. The variance will return to the stationary mode after the shock and remains so until another unexpected change happens.

The plots give indication of some periodic hikes in the variances of the series over time. Commonly, we observe that with the exception of Botswana and perhaps Ghana, higher amplitudes of variances are observed for all series between 2008-2009, just around the time of the global financial crisis. For BCOM, MSCI-DW, MSCI-EM, South Africa, and Southern Africa, the variance changes appear relatively normally distributed than in other markets. We also notice some common volatility patterns among the North African markets (i.e. regional and country-specific), excluding Tunisia; and between Nigeria and the West African regional index.

Table 3.0A: Descriptive statistics of returns (in volatilities).

MARKET	MEAN	MEDIAN	MAX	MIN	SD	SKEWNESS	KURTOSIS
BCOM	0.00840	0.00623	0.06805	5.75E-07	0.00768	2.15808	10.48957
Botswana	0.00475	0.00174	0.16030	0.00000	0.00960	6.59109	71.80905
East Africa	0.00099	0.00062	0.01404	0.00000	0.00125	3.60608	23.68089
Egypt	0.01098	0.00663	0.10872	0.00000	0.01381	2.24040	9.89134
Ghana	0.00475	0.00115	0.12794	0.00000	0.00975	5.08197	41.33031
Kenya	0.00678	0.00457	0.11107	0.00000	0.00799	3.99988	30.78695
Morocco	0.00926	0.00652	0.08724	0.00000	0.00953	2.48508	12.60178
MSCI-DW	0.00693	0.00477	0.17273	0.00000	0.00819	5.70642	80.12100
MSCI-EM	0.00872	0.00620	0.10073	0.00000	0.00960	3.53295	23.50349
Nigeria	0.00938	0.00657	0.10439	0.00000	0.00962	2.56333	15.74459
North Africa	0.00075	0.00049	0.00840	2.30E-07	0.00086	2.87675	15.28979
South Africa	0.01275	0.00940	0.12889	0.00000	0.01273	2.78652	16.66531
Southern Africa	0.01261	0.00912	0.12880	0.00000	0.01260	2.85350	17.25407
Tunisia	0.00508	0.00379	0.06357	0.00000	0.00494	2.88441	18.95112
West Africa	0.00871	0.00644	0.07935	0.00000	0.00819	2.33077	13.01315

The table shows descriptive statistics for the African stock markets as well as regional and global markets in volatilities, from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.

In Figure 3.1, following the work of Zeileis *et al*., (2003), we further check the datasets for the presence of multiple structural changes (shocks).[37] In doing so, we initially consider a self-generated linear regression model expressed as:

$$y_i = x_i^{|} \beta_i + u_i, \qquad for \;\; i = 1, 2, ..., n \tag{3.6}$$

where; y_i denotes the observation of the response variable at time i; x_i is a $k \times 1$ vector of regressors; β_i is the corresponding vector of coefficients for the regressor; and u_i represent the disturbance at time i. The test detects the presence of multiple shocks by using the regression equation in (3.6) to verify whether the coefficients remain constant or do not shift severally from a stable regression relationship to another. The latter phenomenon assumes the presence of *m* change/break points (shocks), where there exist *m*+1 segments in which the coefficients of the regression are constant. To detect the set of breaks/shocks, equation (3.6) is re-specified as:

$$y_i = x_i^{|} \beta_j + u_i, \qquad for \;\; i = i_{j-1} + 1 ..., i_j \;\; and \;\; j = 1, ..., m+1 \tag{3.7}$$

where; the *m*-partition or the collection of shocks represented by $\mathrm{I}_{m,n} = \{i, ..., i_m\}$ for which in normal practice $i_0 = 0$ and $i_{m+1} = n$; and j denotes the segment index.

[37] See also Boako *et al.,* (2016).

Table 3.0B: Summary statistics of bilateral exchange rates expressed in Euros (€) and US Dollars ($)

	Botswana		Egypt		Ghana		Kenya		Morocco		Nigeria		South Africa		Tunisia	
	€	$	€	$	€	$	€	$	€	$	€	$	€	$	€	$
Mean	0.0058	0.0061	0.0048	0.0011	0.0062	0.0037	0.0057	0.0033	0.0012	0.0037	0.0059	0.0029	0.0070	0.0080	0.0028	0.0035
Median	0.0044	0.0044	0.0036	0.0004	0.0045	0.0016	0.0041	0.0018	0.0008	0.0028	0.0041	0.0009	0.0053	0.0062	0.0015	0.0026
Maximum	0.1160	0.1196	0.1584	0.1551	0.1218	0.0654	0.0622	0.0556	0.0171	0.0616	0.1163	0.1198	0.0822	0.0922	0.1014	0.0315
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Std. Dev	0.0061	0.0075	0.0051	0.0035	0.0072	0.0061	0.0057	0.0046	0.0013	0.0034	0.0069	0.0066	0.0066	0.0075	0.0074	0.0032
Skewness	5.7591	5.3404	10.0758	29.1408	5.4785	3.9428	2.5539	4.0047	3.9301	2.9670	4.7548	6.5630	2.3559	2.4331	10.2898	2.0871
Kurtosis	79.778	57.676	275.037	1213.476	59.425	24.399	14.427	28.088	31.533	34.125	46.437	66.781	13.882	15.243	119.536	11.5992

The table shows descriptive statistics for the bilateral exchange rates expressed in Euros (€) and US Dollars ($) in volatilities, from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.

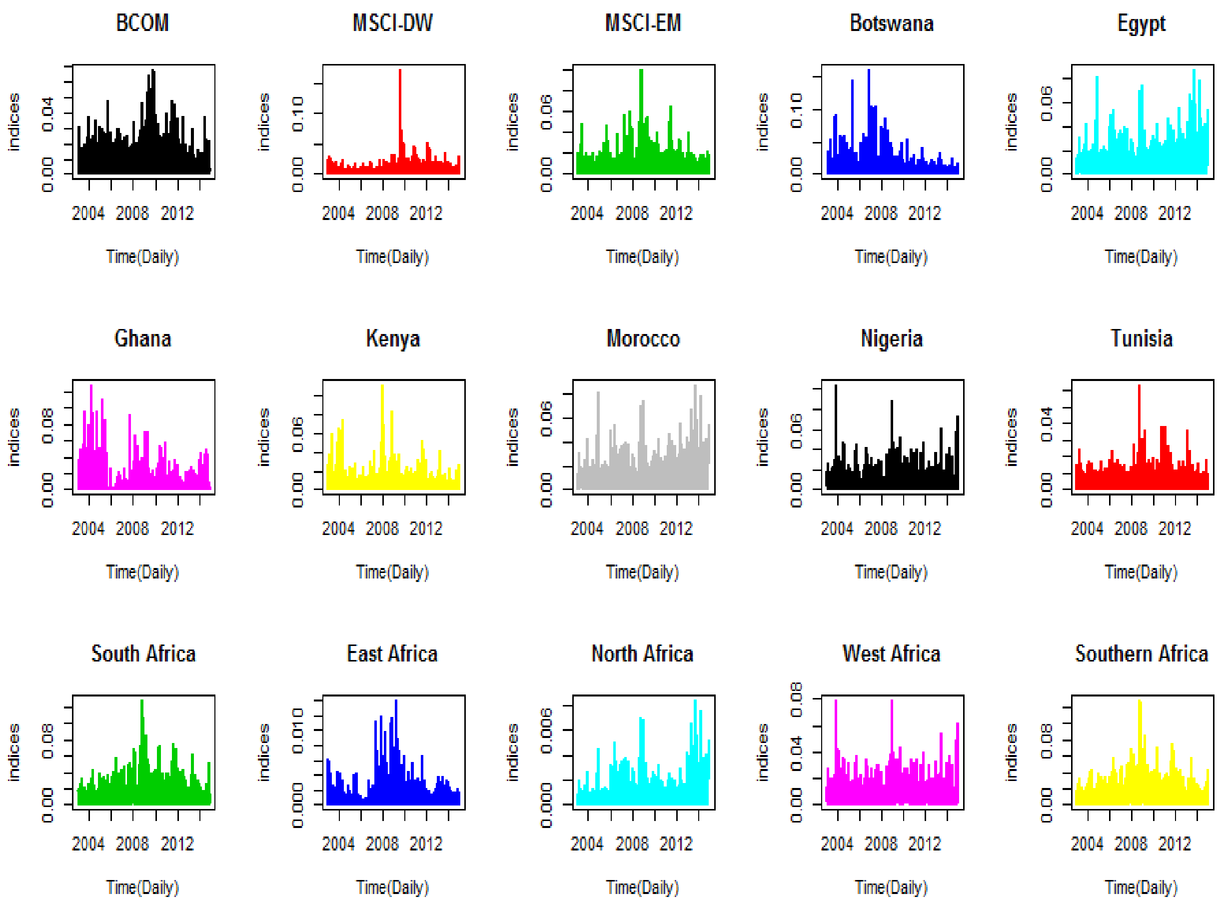


Figure 3.0: Daily volatility changes in country and regional stock markets in Africa as well as global market indices.

Figure 3.1 depicts plots of *m*-segment models for all variables under examination. The optimal model in this case implies selection of the optimal *m* number of changes (shocks) which are selected using the Bayesian Information Criteria (BIC). *Appendix 3.0* presents the BIC-based selected optimal number of *m*-break points, the break point spots and the associated break dates for each variable. From the results shown in *Appendix 3.0*, we notice that excluding Botswana, Ghana, Nigeria, and West Africa, which had two volatility changes each, all other markets had three changes. It can also clearly be observed that, most of the volatility shocks (changes) occurred between mid-2007 and 2012. Exceptions are MSCI-EM, Egypt, North Africa, and Morocco where changes started in 2006.

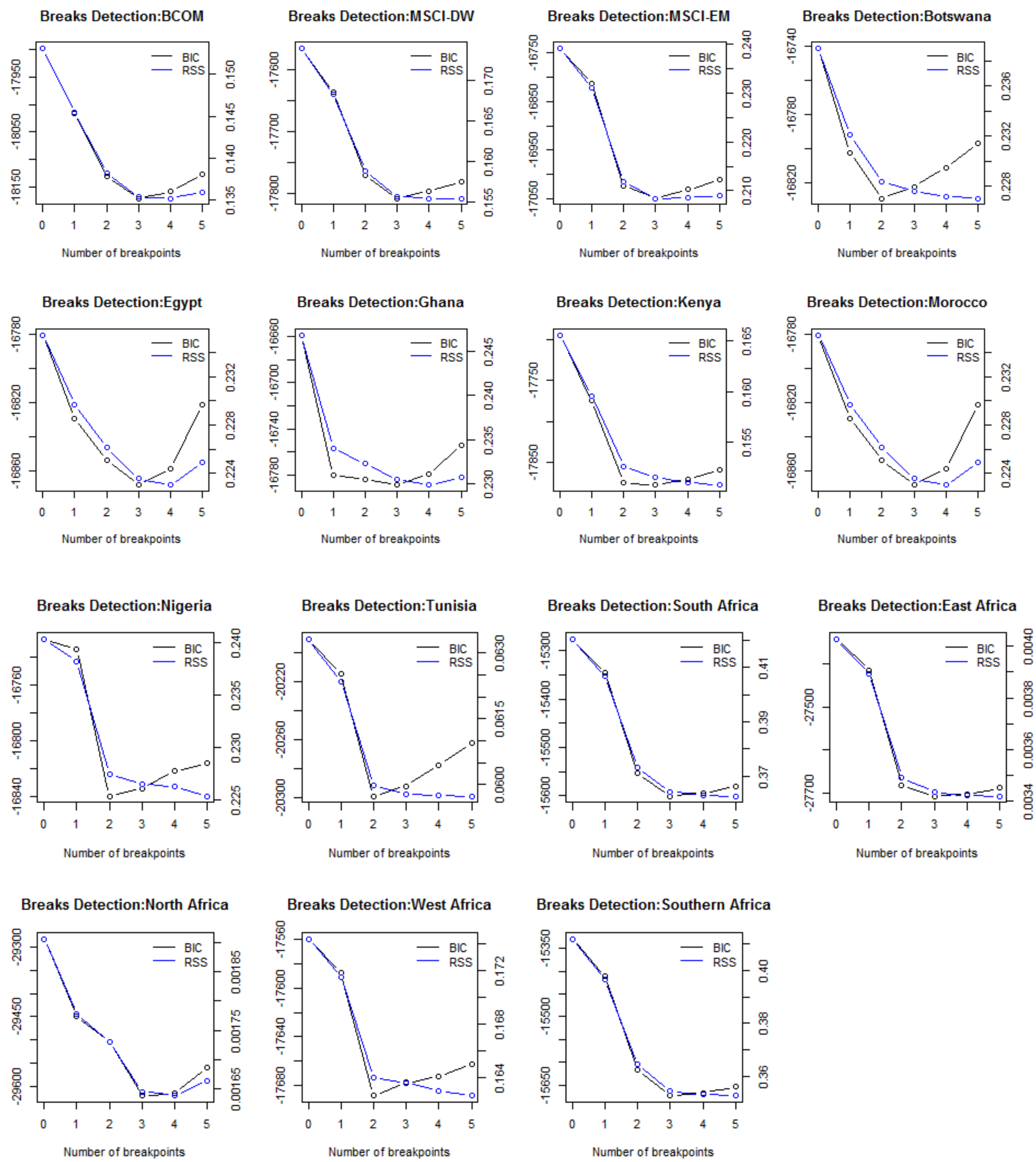


Figure 3.1: Detection of multiple structural shocks (changes) with BIC

Stronger co-movements are therefore expected around these periods. Volatility changes for both African and global markets in 2008 occurred some few months just before the collapse of Lehman Brothers in September, 2008.

3.3 Empirical results of the wavelet power spectrum, coherency, and phase difference

Prior to the wavelet analysis, we present results of Pearson correlations of all variables in Tables 3.1 and 3.2 to examine the degree of association of African stocks with global and regional counterparts, as well as the bivariate exchange rates, and the commodities index. Table 3.1 shows the correlations of markets with exchange rates whilst Table 3.3 shows correlations among markets (that is individual domestic markets, global markets, and the commodities market). Panels A and B of Table 3.1, respectively show the correlations of all markets with currencies expressed in Euro and US dollars. The results show that approximately 89.8% of the volatility correlations in Panel A are below 0.05 and in Panel B about 87.6% are below 0.05.

Thus, both individual country markets, as well, as regional and global markets show low levels of volatility co-movements with the bilateral exchange rates. In contrast to Table 3.1, we note that 70.8% of the correlation coefficients in Table 3.2 exceed 0.05; with 96.1% between the North Africa regional market and that of Morocco, 97% between the West Africa regional bourse and Nigeria, and 99.9% between South Africa and the Southern African market. The results show that correlations among stock markets and between stock markets and commodities are stronger than between stock markets and currencies.

Although graphical plots, detection of volatility changes, and Pearson correlations have aided in identifying some levels of co-movements, wavelets are believed to offer superior results. Wavelet analysis is able to derive all information about structural changes in the data through a phase difference technique (Aguiar-Conraria and Soares, 2011). Further, unlike wavelets, the correlation analysis is unable to provide information about when correlations occur and lead-lag relationships - having different data series showing similar periodicities does not necessarily connote lead-lag relationship (Pinho and Madaleno, 2011).

In Figure 3.2, we employ the wavelet power spectrum (WPS) as a measure of the local variance of the underlying series. The WPS is presented in plots with contours in time and frequency axes indicated on the horizontal and vertical axes, respectively. Throughout this chapter, time is expressed in years for ease of interpretation.

Table 3.1: Correlations of markets with bilateral exchange rates

Markets	Botswana	Egypt	Ghana	Kenya	Morocco	Nigeria	South Africa	Tunisia
Panel A: Bilateral exchange rates expressed in Euros (€)								
Botswana	0.0049	-0.0228	-0.0168	-0.0024	-0.0275	-0.0336	-0.0021	-0.0422
Egypt	0.0465	0.0084	-0.0025	0.0262	0.0416	0.0370	0.0457	-0.0122
East Africa	-0.0016	-0.0274	-0.0168	-0.0253	-0.0097	-0.0172	0.0102	-0.0355
Ghana	0.0205	0.0073	0.0147	0.0029	0.0135	-0.0208	0.0392	-0.0046
Kenya	-0.0001	-0.0232	-0.0544	-0.0505	-0.0162	-0.0321	-0.0273	0.0134
Morocco	-0.0181	-0.0441	-0.0235	-0.0002	-0.0579	-0.0308	-0.0306	-0.0105
Nigeria	-0.0086	-0.0364	-0.0106	-0.0222	-0.0373	-0.0356	-0.0179	-0.0334
North Africa	-0.0231	-0.0601	-0.0365	-0.0043	-0.0834	-0.0563	-0.0433	-0.0355
South Africa	-0.0286	-0.0697	-0.0612	-0.0548	-0.0581	-0.0600	-0.0175	-0.0517
Southern Africa	-0.0281	-0.0697	-0.0623	-0.0556	-0.0565	-0.0609	-0.0165	-0.0514
Tunisia	0.0214	-0.0004	0.0066	0.0146	0.0724	0.0095	0.0318	-0.0186
West Africa	-0.0070	-0.0340	-0.0095	-0.0210	-0.0372	-0.0440	-0.0196	-0.0415
BCOM	-0.0309	0.0392	0.0117	0.0049	-0.0292	-0.0377	-0.0141	-0.0205
MSCI-DW	0.0173	0.0018	0.1151	0.0302	0.0543	-0.0311	-0.0223	-0.0476
MSCI-EM	-0.0229	-0.0768	-0.0703	-0.0622	-0.0603	-0.0727	-0.0445	0.0457
Panel B: Bilateral exchange rates expressed in US Dollars ($)								
Botswana	0.0814	-0.0189	-0.0171	0.0361	-0.0176	-0.0154	-0.0181	0.0049
Egypt	0.0220	0.1266	-0.0192	0.0149	0.0362	0.0223	0.0466	0.0481
East Africa	0.0442	-0.0284	-0.0017	0.0324	-0.0584	-0.0434	-0.0213	-0.0374
Ghana	0.0401	-0.0171	-0.0274	0.0199	0.0299	-0.0250	0.0417	0.0161
Kenya	0.0726	-0.0140	-0.0279	-0.0416	-0.0423	0.0258	0.0221	-0.0724
Morocco	0.0037	-0.0272	-0.0358	-0.0297	-0.0164	-0.0067	-0.0572	0.0048
Nigeria	0.0007	-0.0193	-0.0135	0.0171	-0.0535	-0.0540	-0.0633	-0.0198
North Africa	0.0105	-0.0498	-0.0482	-0.0267	-0.0516	-0.0147	-0.0661	-0.0087
South Africa	0.0823	-0.0173	-0.0423	-0.0173	-0.0576	-0.0745	-0.0367	-0.0532
Southern Africa	0.0840	-0.0167	-0.0425	-0.0171	-0.0562	-0.0741	-0.0372	-0.0540
Tunisia	0.0680	-0.0324	-0.0334	-0.0035	-0.0420	0.0097	-0.0075	0.0077
West Africa	0.0129	-0.0275	-0.0255	0.0231	-0.0556	-0.0598	-0.0693	-0.0221
BCOM	0.0402	0.0619	0.0547	0.0066	0.0026	-0.0393	-0.0184	-0.0384
MSCI-DW	0.0145	-0.0023	0.0994	0.0960	-0.0043	0.0036	0.0237	-0.0074
MSCI-EM	0.0357	-0.0084	-0.0378	-0.0246	-0.0539	-0.0450	-0.0192	-0.0958

The table depicts the Pearson correlation coefficients for volatilities from 3rd January, 2003 to 29th October, 2014. Volatilities are based on absolute returns.

We express frequency in powers of two, ranging from lower, 4 days (bottom of the plot) to upper, 2048 days (top of the plot). In the WPS, thick white contours in regions of energy denote significance at the 5% (95% confidence) level. Following a white noise process, the WPS is estimated from Monte Carlo simulations. To the right of the WPS is a colour bar depicting the steep power gradient of the significant contours ranging from blue (lower power) to red (higher power). The *n-shaped* cone indicates the region of influence affected by edge effects. Periods outside the cone do not represent statistical confidence and are not considered for analysis.

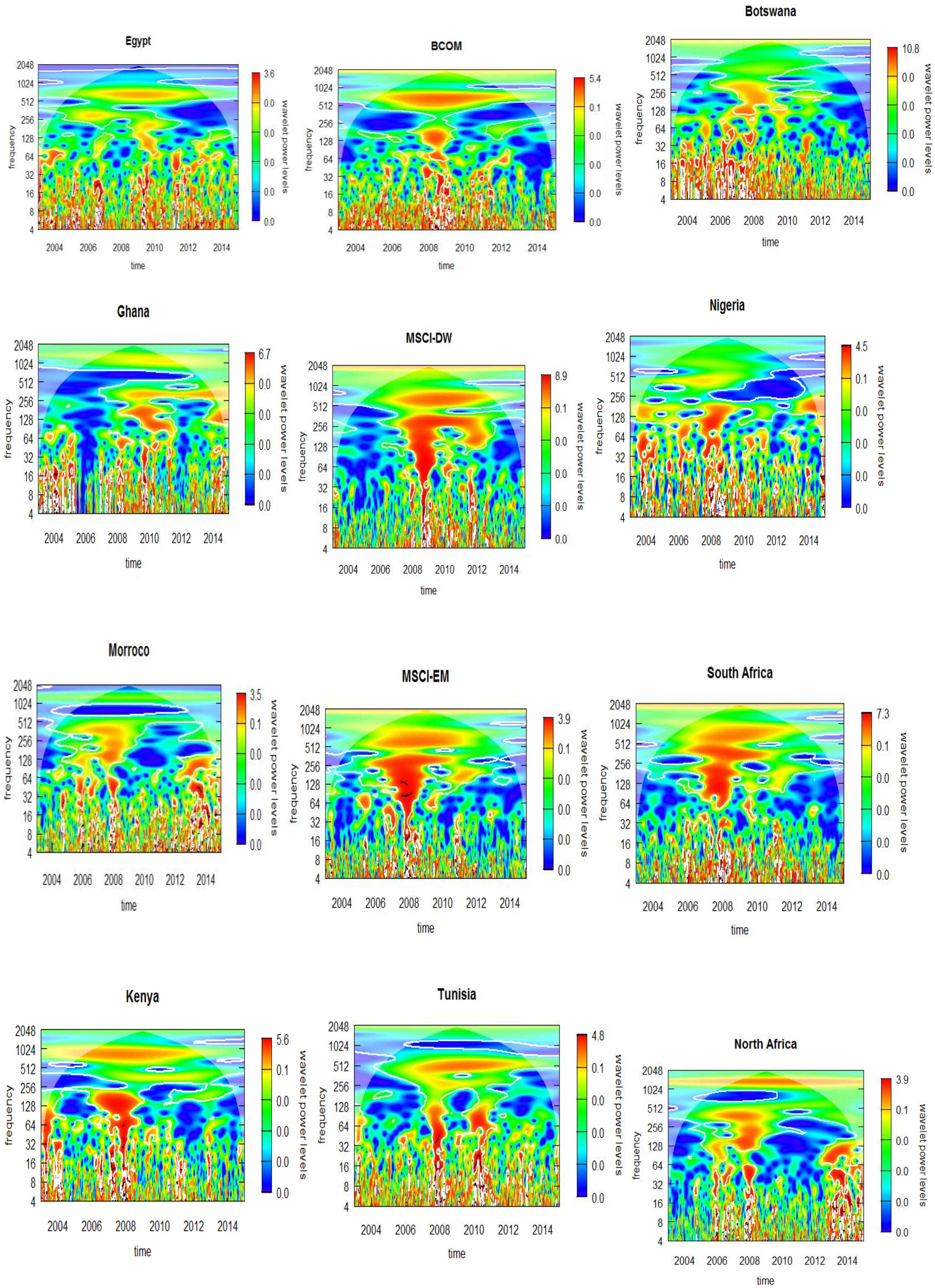
Table 3.2: Correlations of volatility of returns

	BCOM	Botswana	East Africa	Egypt	Ghana	Kenya	Morocco	MSCI-DW	MSCI-EM	Nigeria	North Africa	South Africa	Southern Africa	Tunisia	West Africa
BCOM															
Botswana	*0.0815*														
East Africa	*0.0974*	*0.0564*													
Egypt	*0.0179*	*-0.0112*	*0.0105*												
Ghana	*-0.0008*	*0.3133*	*-0.0134*	*0.0215*											
Kenya	*0.0544*	*0.1498*	*0.0961*	*-0.0225*	*0.0156*										
Morocco	*-0.0031*	*0.0919*	*0.0627*	*-0.0267*	*-0.0074*	*0.0285*									
MSCI-DW	*0.0774*	*0.0465*	*0.0739*	*0.0131*	*0.0084*	*-0.0107*	*-0.0328*								
MSCI-EM	*0.1077*	*0.0877*	*0.1867*	*-0.0420*	*-0.0199*	*0.1835*	*0.0307*	*0.0390*							
Nigeria	*0.0547*	*0.0610*	*0.1045*	*0.0039*	*0.0189*	*0.0871*	*0.0411*	*0.0379*	*0.0792*						
North Africa	*-0.0017*	*0.0982*	*0.0941*	*-0.0330*	*0.0051*	*0.0445*	*0.9605*	*-0.0307*	*0.0567*	*0.0587*					
South Africa	*0.1097*	*0.2138*	*0.2240*	*-0.0511*	*-0.0053*	*0.1147*	*0.1415*	*0.0694*	*0.1861*	*0.0846*	*0.1504*				
Southern Africa	*0.1143*	*0.2217*	*0.2263*	*-0.0494*	*-0.0046*	*0.1587*	*0.1408*	*0.0716*	*0.1897*	*0.0852*	*0.1485*	*0.9988*			
Tunisia	*0.0921*	*0.1270*	*0.1321*	*-0.0066*	*0.0268*	*0.0658*	*0.1065*	*0.0032*	*0.0807*	*0.0311*	*0.1103*	*0.2461*	*0.2492*		*0.1169*
West Africa	*0.0596*	*0.1752*	*0.1061*	*0.0057*	*0.1692*	*0.0927*	*0.0558*	*0.0391*	*0.0887*	*0.9700*	*0.0759*	*0.1065*	*0.1077*	*0.0595*	

The table depicts the Pearson correlation coefficients for volatilities from 3rd January, 2003 to 29th October, 2014. Volatilities are based on absolute returns.

In Figure 3.2, majority of the variances happen at lower-to-medium frequencies. It is noticed that significantly high variance concentration exist for BCOM between 2004 and 2006; and 2008-2012. The Egyptian stock market shows similar features. These power events appear stronger from early 2008 to late 2009 across the 4-128 day frequency bands. The relatively high power between 2008 and 2009 corresponds to the recent global financial crisis (GFC) that characterized extreme price fluctuations and higher variances in the commodities markets. The WPS plot of MSCI-DW depicts strong significant power effect in the daily frequency band of 4-256 from early 2008 to early 2009. Similar result is found at mid-2010 and early 2012. For MSCI-EM, we notice sparingly significant power events from the early parts of 2007 through to beginning of 2008 across the 4-64 day frequency band. An important feature worth mentioning from the WPS plots is that stronger variances are averagely observed around the period of the 2007-2009 GFC. We also notice from all the plots that strong variance concentration is found at low-to-medium frequencies whilst weak variance concentrations are found at relatively higher frequencies.

Though the WPS helps us to identify regions in the distribution of all series where the variances of stock market and commodity indices were higher, it fails to identify co-movement and lead-lag relationships capable of determining causality between two series. Possible means of mitigating this shortfall are the resort to wavelet cross power spectrum (WCPS) or wavelet squared coherency. However, we decline the use of WCPS because it can sometimes yield misleading results (Pinho and Madaleno, 2011). Roesch and Schmidbauer (2014) recommend the use of wavelet coherence, rather than WCPS. The wavelet coherence, like the coefficient of determination adjusts for individual (one-dimensional) power difference in two series and provides joint periodic properties of the series (Roesch and Schmidbauer, 2014). Per the nature of our datasets (i.e. having long span over 12 years), it may be worthwhile to examine how co-movements have evolved over time. Again, to be able to make inferences for short and long term investment horizons, it is useful to examine whether or not co-movements vary in the frequency-time domains. To achieve these objectives, we resort to the use of the wavelet squared coherency as a measure of local correlation among variables; and phase differences to depict any lag or lead relationships between components in subsequent sub-sections.


Egypt
BCOM
Botswana
Ghana
MSCI-DW
Nigeria
Morroco
MSCI-EM
South Africa
Kenya
Tunisia
North Africa
frequency
time
wavelet power levels

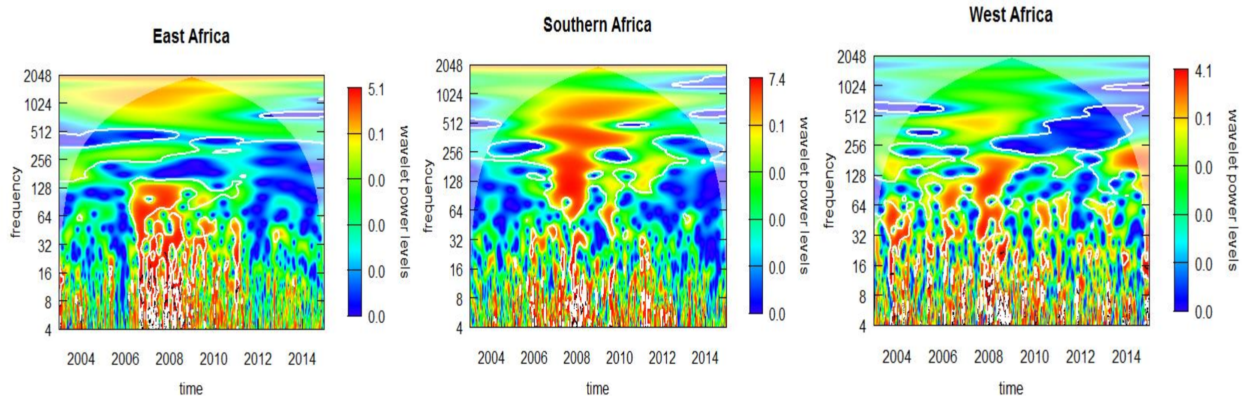


Figure 3.2. This figure shows the wavelet power spectrum of the volatilities of selected individual and regional African stock markets, developed and emerging stock markets, as well as the commodities markets, from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.

3.3.1 Analysis of global co-movements

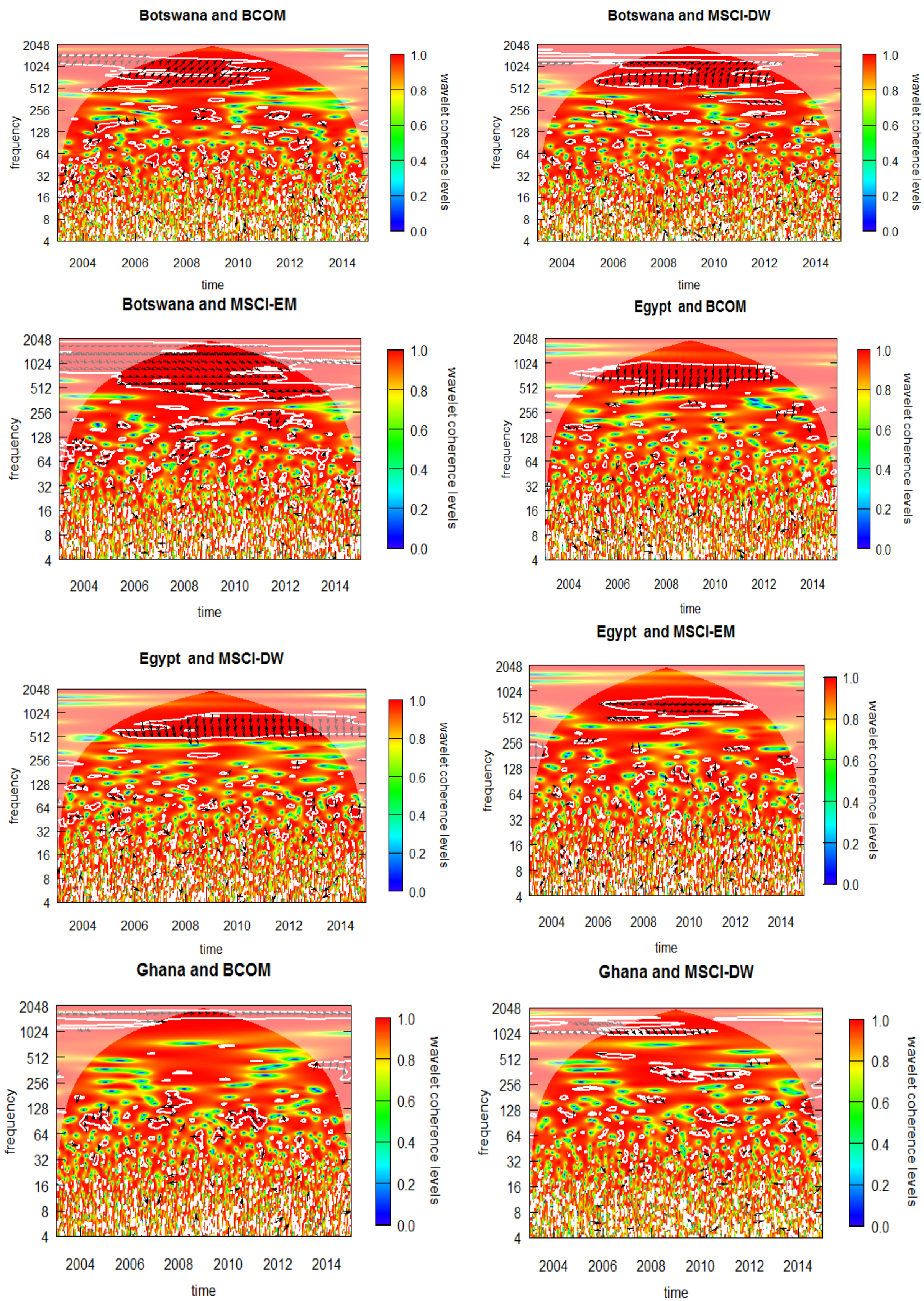
We show wavelet squared coherency and phase difference between each considered African equity market's volatility of returns with those of developed and emerging stock markets, and the global commodities market in Figure 3.3. Coherency is shown using contour plots as it involves three dimensions. In Figure 3.3, the vertical and horizontal axes respectively denote frequency and time with frequency in daily ranges from lower (4 days) to upper (2048 days). The cone of influence showing the region of edge effects contains white contour lines which signify the region of 5% significance level simulated using Monte Carlo method of two white noise series with Bartlett window type. Again, the vertical bar to the right of the coherence and phase difference plots denotes colour codes for local correlations (coherence) ranging from red (high coherence) to blue (low coherence). Thus, in our framework, red colour inside the white contour at the bottom (top) of the plots represents strong co-movement at low (high) frequencies, whilst red colour in the white contours at the left-hand (right-hand) side symbolizes strong co-movement at the beginning (end) of the sample period. The phase difference between two series is indicated by arrows. The name of the index shown first is the first series and the other being the second,[38] on account that the order is needed for the validity of the model (Madaleno and Pinho, 2012). *Arrows pointing to the right suggest that the series are in phase. To the right and up means the first series is lagging. Arrows to the right and down means the first series is leading. Arrows pointing to the left mean that the two series are out of phase. To the left and up shows the first series is leading. To the left and down shows that the first series is lagging*. Plots of the wavelet squared coherency and phase differences present some exciting results.

[38] For example in the cross coherency plot between Ghana and BCOM, Ghana is the first series and BCOM is the second.

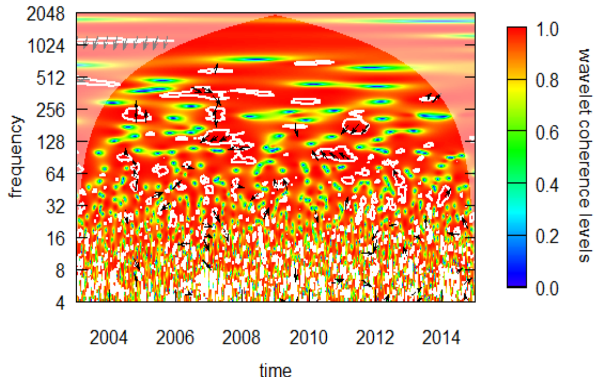
A first glance of all plots shows that there are generally high co-movements across market pairs as the red colour dominates all significant regions. Despite this, most of the stronger and finest coherences stretching over longer periods are found at medium-to-high frequencies. Again, coherency appears periodic and not spread through the entire time distribution of the data span. It is important to note that some of the coherencies fall outside the region of edge effects (cone of influence) and are therefore not significant. No meaningful inferences can therefore be made from such coherences. From the phase difference arrows, the nexus among markets are predominantly non-homogenous across time because arrow vectors point left and right, and up and down regularly. We in turn analyze individual co-movements in the subsequent paragraphs.

For Botswana, we observe a highly and statistically significant co-movement with BCOM in the 512-1024 daily frequency band for late 2005 to late 2010. The series are in phase with BCOM leading Botswana. At daily frequency bands between 32-256, several co-movements occur throughout the entire period (with non-homogenous phase differences), albeit at short periodicities including the period of the 2007-2009 financial crisis at the 130-256 band (at which period Botswana leads BCOM). Similarly, the co-movement between Botswana and MSCI-DW is very strong at the daily frequency band of 512-1024 from early 2005 to late 2012. During this period, MSCI-DW leads Botswana. However, co-movements observed at early 2007 to end of 2008 at 130-256 bands and between end of 2011 to early 2012 at 65-128 band show Botswana leading MSCI-DW.

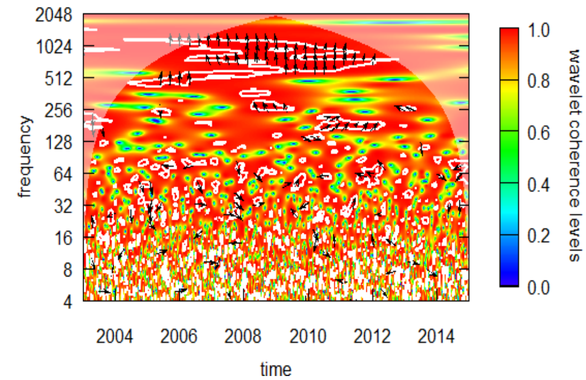
We notice also higher co-movement between Botswana and MSCI-EM from early 2005 to late 2012 at the 480-1040 frequency band with no lead-lag relationship. Between 2007 and 2008 however, MSCI-EM leads Botswana at the 64-128 band, and between 2010 and 2011, we observe Botswana lagging at the 140-256 band. The strong correlations between the Botswana stock market and those of international markets (BCOM, MSCI-DW, and MSCI-EM) supports the findings of Ahmed and Mmolainyane (2014) that the openness of the Botswana market makes capital market development strongly driven by foreign companies. In the 2007-2009 crisis, lower diamond sales to the financially depressed European markets made Botswana's domestic economy highly vulnerable to shifts in


Botswana and BCOM
Botswana and MSCI-DW
Botswana and MSCI-EM
Egypt and BCOM
Egypt and MSCI-DW
Egypt and MSCI-EM
Ghana and BCOM
Ghana and MSCI-DW
frequency
2048
1024
512
256
128
64
32
16
8
4
2004
2006
2008
2010
2012
2014
time
wavelet coherence levels
1.0
0.8
0.6
0.4
0.2
0.0

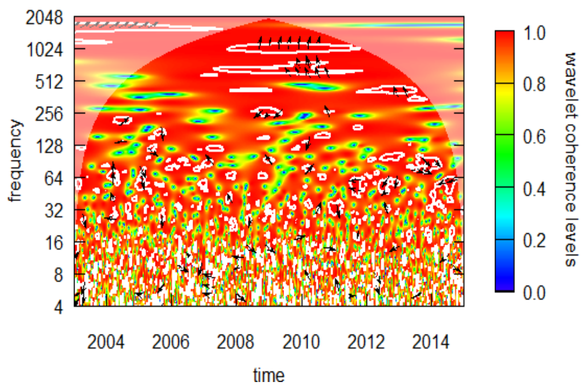
Ghana and MSCI-EM



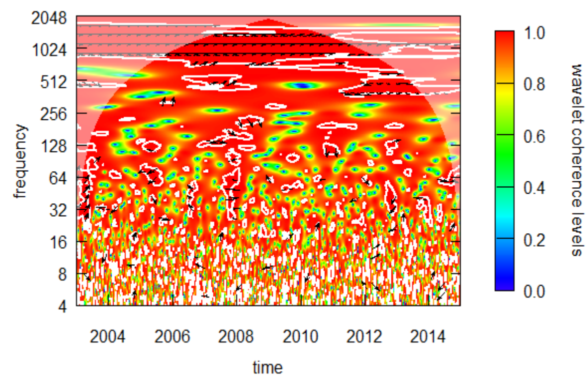
Kenya and BCOM



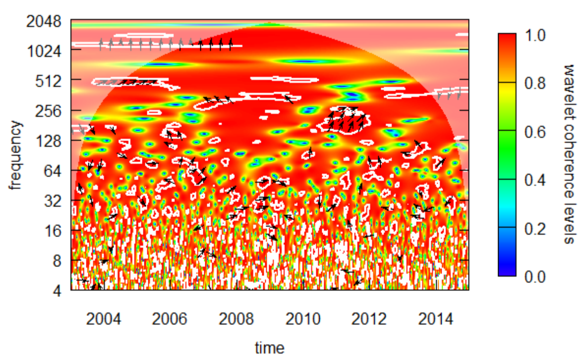
Kenya and MSCI-DW



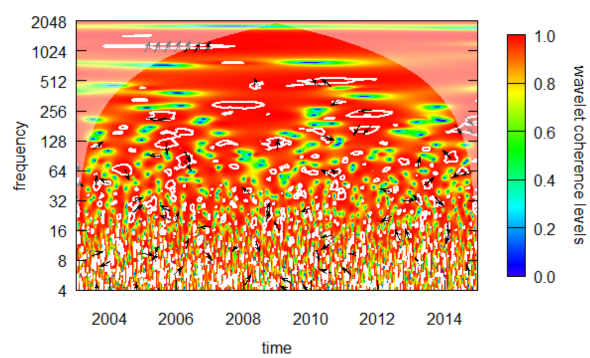
Kenya and MSCI-EM



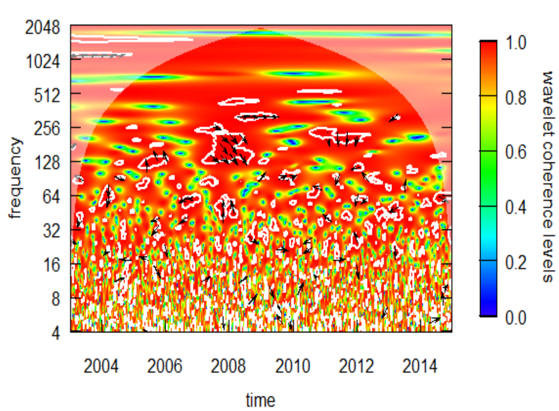
Morroco and BCOM



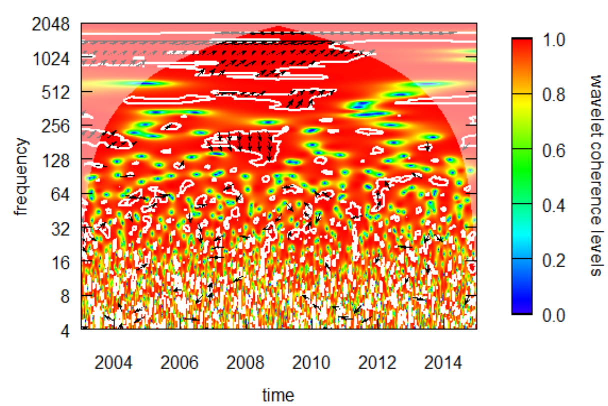
Morroco and MSCI-DW



Morroco and MSCI-EM



Nigeria and BCOM



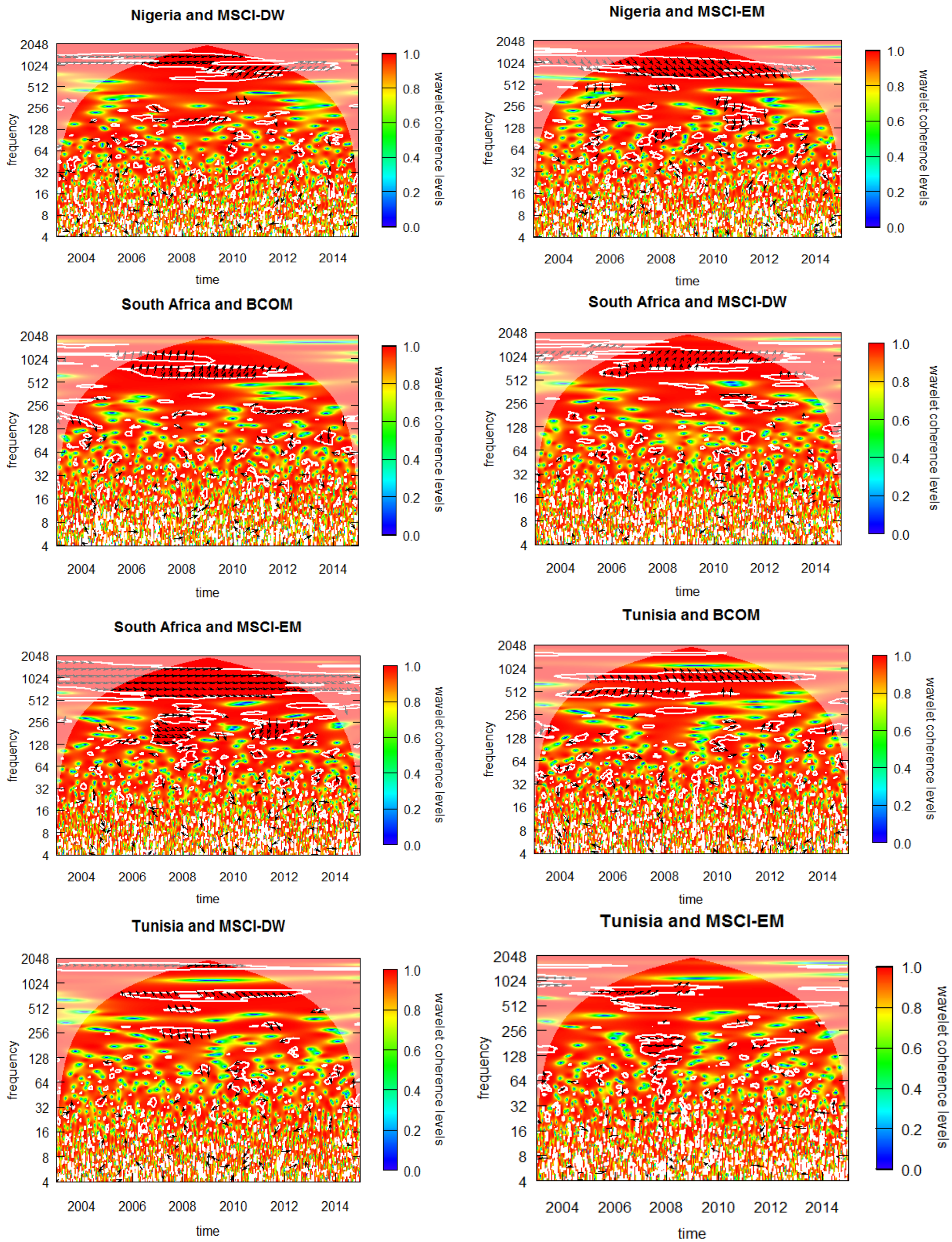


Figure 3.3. This figure shows the cross-wavelet squared coherency and phase difference plots between the African stock markets volatility on one hand and those of MSCI-DW, MSCI-EM, and BCOM on the other hand from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.

global economies that consume the country's diamond (see also Ahmed and Mmolainyane, 2014). Therefore business cycle fluctuations of international investors consequentially caused significant changes on the Botswana equity market, thereby drawing correlations with global counterparts to unity.

It is important to stress that though significant co-movements exist between Egypt and the markets under consideration, the finest of such co-movements are highly noticeable with BCOM and MSCI-DW. The co-movements of the Egyptian stock market and each of BCOM and MSCI-DW occur at the higher frequency band of roughly 480 to 1000; and stretch over the period of 2005 to end of 2012.

Between Ghana and BCOM, the 5% significant contours depict sparsely stronger co-movements at the 64-130 daily frequency bands occurring at short periodicities. The first noticeable co-movement happens in 2004 with a somewhat non-homogenous phase difference. From early 2007 to late 2008, and between the early periods of 2010 and 2011, we notice separate co-movements in which Ghana leads in the latter case. At a high frequency of 1024, the Ghana-MSCI-DW co-movement (though relatively light) stretches from early 2006 to early 2010 with Ghana lagging. However, towards the middle frequency band (256-508) the co-movement is limited to between early 2008 and early 2012 with Ghana leading. For Ghana MSCI-EM, pockets of higher co-movements with varying phases occur at the 64-510 daily band.

The Kenyan stock market index returns shows stronger co-movements with those of BCOM, MSCI-DW, and MSCI-EM at high frequencies and longer periodicities with some islands of coherency occurring in the middle frequency belts at shorter periods. In all, the Kenya-BCOM and Kenya-MSCI-EM co-movements stretch over relatively longer periods from 2006-2012, whereas for the Kenya-MSCI-DW coherency at the high daily frequency band of 512-1024 starts from late 2008 to late 2010. The phase difference vectors suggest no lead-lag relationship for Kenya-MSCI-EM. In the case of the Kenya-BCOM however, Kenya leads the nexus from late 2006 to early 2009, whilst the part of the coherency occurring between 2009 and 2012 is led by BCOM. Mixed phase difference results are seen for Kenya-MSCI-DW for the 512-1030 frequency band co-movement.

We observe shorter and very thin periodic stronger co-movements of the Casablanca stock market in Morocco with those of the markets under consideration. Mainly, the biggest contours indicating the 5% significance of these co-movements happen at the 128-256 daily frequency bands. For instance, we record stronger co-movement between Morocco and BCOM within year 2011 at the 130-256 band in which BCOM leads. In the case of Morocco-MSCI-EM, stronger co-movement is noticed at the 128-256 daily band from early 2007 to early 2008. It is instructive to note that in the case of Morocco, we do not see any major co-movement with the global markets during the 2007-2009 GFC suggesting some kind of insulation from global volatility shock spillovers of the Casablanca market.

Nigeria generally shows higher degrees of co-movements at high frequencies with the global markets. We notice that from late 2006 to early 2012, the Nigerian stock market index is highly integrated with that of the commodities index (BCOM) at the daily frequency band of 530-1030 with Nigeria lagging. Perhaps due to the oil price boom and bust during the GFC, we observe stronger co-movements at the 100-150 daily bands from early 2007 to late 2008 in which Nigeria leads. Between 2007 and 2012 at 520-1020 daily bands and from early 2008 to end of 2009 at 128-140 daily bands, Nigeria lags in a stronger co-movement with the MSCI-DW index. Additionally, the longest periodic co-movement of the variance of the Nigeria bourse is seen with that of the MSCI-EM index from early 2007 to early 2013 in which Nigeria leads.

Except for the South Africa-MSCI-EM in which co-movement is in phase, South Africa lags in the co-movement with BCOM and MSCI-DW at the 512-2040 daily frequency bands. At the same frequency bands, co-movements of all the global markets with the South African equity market stretches over longer periods roughly from early 2005 to late 2012. South Africa's integration with the global markets is thus not evolving today. Apart from the above, the South African market also shows stronger co-movement with the MSCI-EM at the 128-256 bands from early 2007 to mid-2008 (with no lead-lag relationship) and from early 2011 to late 2012 (in which case South Africa lags). The strong linkages of the South Africa market with global counterparts may reflect its higher levels of integration, market liquidity, or shocks from the real sector. For example, as noted by Simatele (2014), the effect of the 2007-2009 global financial crisis on South Africa's economy was felt through a deteriorating overall economy which heightened pressure on the country's balance of payment with consequential effects on domestic exchange rates, overall gross domestic product (GDP) and financial sectors, without corresponding increases in portfolio investments flows.

The Tunisian stock market appears to share longstanding cross-market volatility effects with BCOM and MSCI-DW index than with the MSCI-EM index at high frequencies. At the 530-1024 bands, Tunisia leads in the co-movement with BCOM from early 2005 to late 2012. However, at the 512 band, Tunisia lags in its co-movement with the BCOM. At the 512-800 bands, Tunisia leads in the co-movement with MSCI-DW from early 2005 to late 2012. Between Tunisia and MSCI-EM, we do not witness longer periodic co-movements except the islands of high coherencies occurring in 2008 at the 128-240 bands and the co-movement from 2006 to 2008 at the 512-540 daily frequency bands.

In all, co-movement among markets (Africa and global) is dynamic as it is time-varying. The co-movements however, appear partially segmented, as most domestic markets show lower degrees of coherencies with global counterparts at varying periods. The evidence of partial segmentation may reflect low levels of foreign investors' participation in the domestic markets fueled by problems of home bias, high inflation, exchange rate exposures; and other factors such as constraints relating to poor governance structures, macroeconomic unsteadiness, small market sizes, lack of liquidity, political unrest, etc. For instance, despite the increases in private capital flows into Sub-Saharan Africa (SSA) in the early days of the 21st century, the advent of the GFC registered some declines due to increased investor risk-aversion, tighter global credit conditions, and developments in the bond markets (Simatele, 2014). Despite this, the recorded episodes of time varying incremental co-movement towards the end of the data may be explained by aggressive pursuit of integration on the continent. This has been realized through gains in the removal of some barriers to intra-regional trade, market openness and increased cross-border portfolio capital flows, as well as improvements in overall economic integration.

Interestingly, longer periodic co-movements are felt at higher frequencies. Additionally, short cycle coherencies are also noticed in some cases largely at medium daily frequency bands. Phase difference arrow vectors give indication of lead-lag (non-homogeneous) relationships suggesting negative correlations as in most cases, arrows point left or right, and up and down. Homogeneous arrow vectors indicate positive relationships. We wish to emphasize that lead-lag relationships in cross-market volatility correlations may enhance diversification and arbitrage opportunities worthy of consideration by international investors (see also, Madaleno and Pinho, 2012).

Our empirical results both support and contradict extant literature. Generally, the results support earlier findings on higher co-movement among international stock markets (e.g. Lee, 2004; Berben and Jansen, 2005, Garham *et al.,* 2012). The generally higher levels of co-movement of some African markets with global counterparts indicate that most equity markets in Africa are highly vulnerable to international market fluctuations – a precursor for global shock contagion. Again, converse to Garham and Nikkinen (2011) and Garham *et al.,* (2012) in which high degrees of co-movements are recorded at lower frequencies (longer periods) between the MSCI-US and MSCI indexes for emerging markets such as Mexico and Peru, we report strong local volatility correlations between global markets and African stock markets at higher frequencies (short-run fluctuations), with some co-movements at the medium frequencies beyond 2006. Because relatively the finest local correlations occur at higher frequencies – largely 512-1024 days, we argue that cross-market volatility spillovers between global and African markets are confined to short-run fluctuations. This is consistent with Lee (2004) and contradicts Madaleno and Pinho (2012) who respectively argue that the most significant impact in cross-market spillovers are captured at higher and lower frequencies. The differences in our results from other studies may be due to differences in the characteristics of markets considered and the span of data.

Another implication of our finding is that, from the perspective of the international investor, equity portfolio diversification opportunities into African markets (specifically, Tunisia, South Africa, Nigeria, Kenya, Egypt, and Botswana) are relatively less significant in the short term than the long term. International investors with long-term investment horizons could therefore diversify into the above markets to reduce portfolio risk by adopting lower frequency trading strategies. The results generally show that stronger co-movements occurring at medium frequencies exist at shorter periods. This appears useful for investors with short term investment needs seeking diversification in the short-to-medium term.

Further observation of the findings is the somewhat sparse co-movement between the MSCI-DW on one hand and each of Ghana and Morocco on the hand across all frequencies and time. We also notice that relatively major stronger co-movements occurring during the period of the 2007-2009

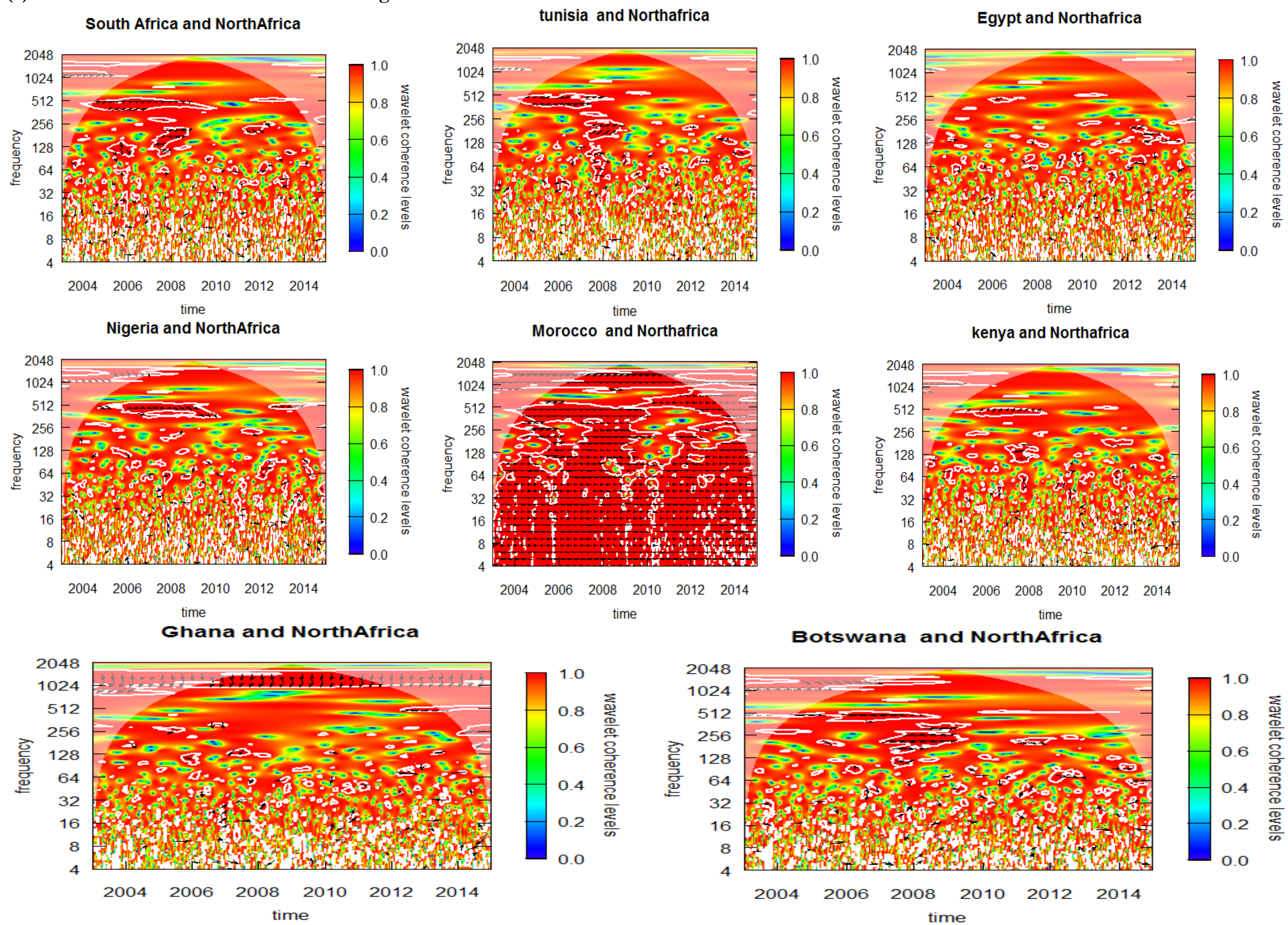
GFC happen at higher frequencies (shorter periods). Moving down the frequency axis, major co-movements are hardly observed across all market pairs for the GFC period. This suggests that the impact of the crisis on international investors diversifying their equity portfolio in Africa's stocks was more severe for investors with short-term than those with long-term investment horizons.

3.3.2 Evidence from regional markets in Africa

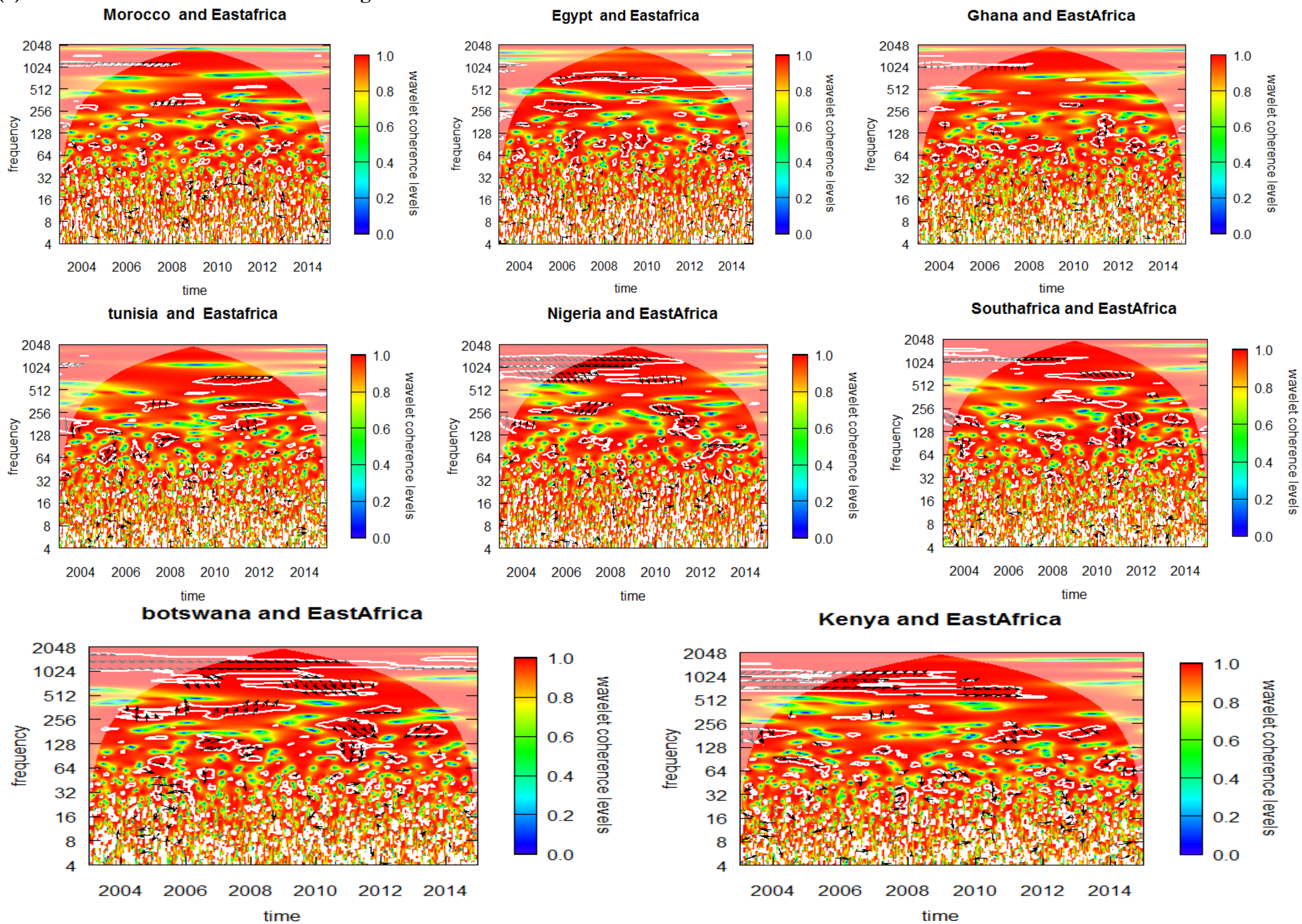
In Figure 3.4a-d, we report results of individual markets co-movements with regional counterparts. Similar to previous results on wavelet coherency in this paper, relatively major significant co-movements occur at higher frequencies. Exceptions are Morocco vs. North Africa, and probably South Africa vs. Southern Africa, where coherencies are both in the high and low frequencies. Consistent with results from Table 3.2, we observe that Morocco shows very strong positive co-movements (since all phase difference arrows are in phase) with the North African regional market. This strong correlation moves across the entire distribution from 2003 to 2014 and at both lower and higher frequencies. Co-movements of all other markets with the North African regional counterpart are relatively sparse.

In East Africa, whereas five markets (Morocco, Egypt, South Africa, Ghana, and Tunisia) sparsely co-move with the regional market, three markets (Nigeria, Botswana, and Kenya) show higher levels of periodic co-movements. Both the Botswana and South Africa stock markets are highly integrated with the Southern African regional market. Botswana's integration with the regional market has evolved over the 2004 to 2012 period at a high daily frequency band of 480-1024. At the middle frequency, however, the co-movement is relatively periodic and not continues. In Table 3.2, we notice a 99.9% correlation of the South African stock market with the Southern African regional market along the entire distribution of the series. Figure 3.4c however indicates that the correlation is time-varying and occurs at high frequencies from 2005 to 2007, whilst between 2008 to early 2012 the correlation revolves around the middle to lower frequency bands. Again, although all other markets outside the Southern African region are highly integrated with the regional market, Kenya and Nigeria are relatively the most integrated. We notice again that markets that are highly integrated with the West African regional counterpart and over longer periods of time are those of Kenya, Botswana, Egypt, and South Africa.

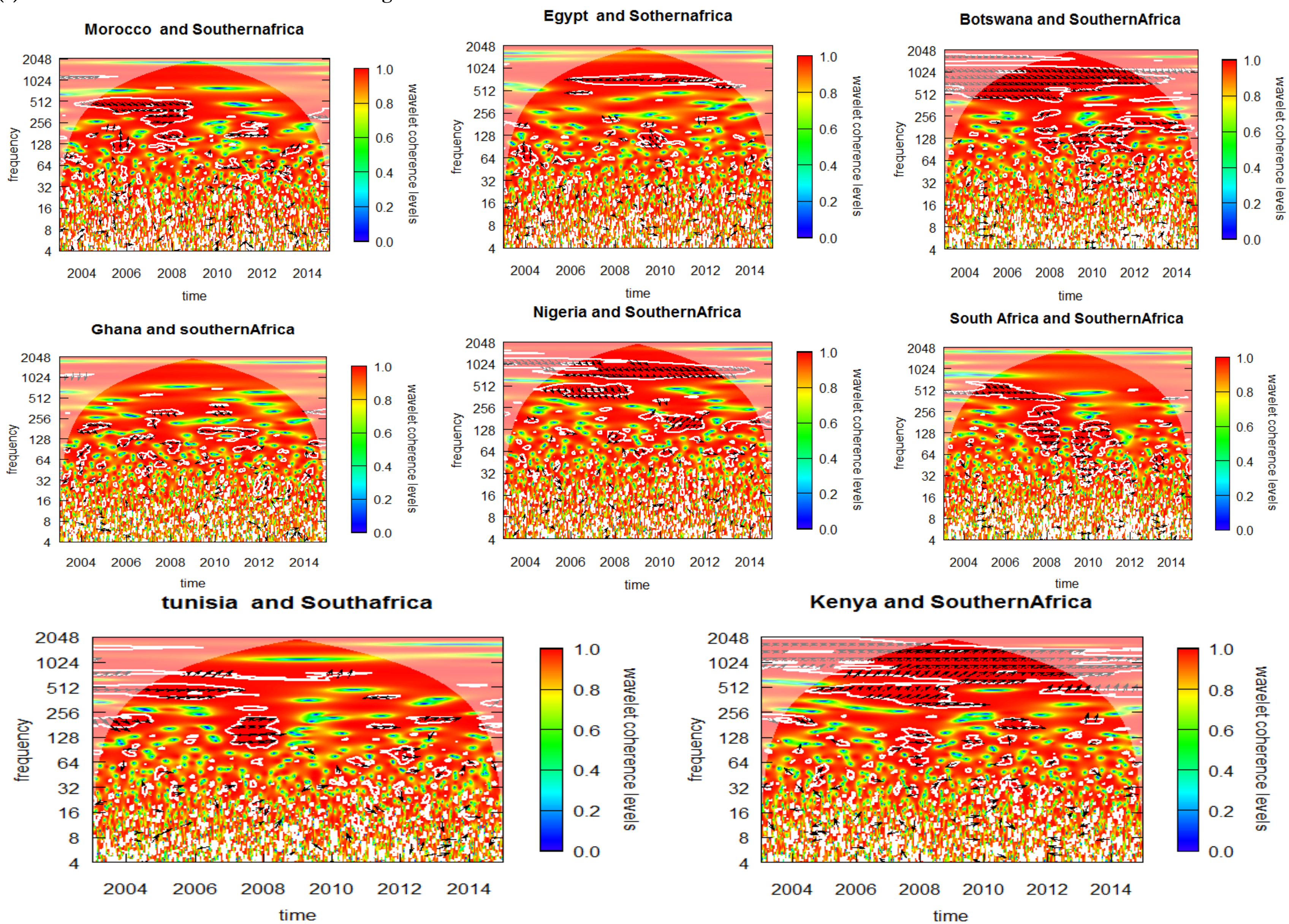
(a) Co-movement with the North African regional market



(b) Co-movement with the East African regional market



(c) Co-movement with the Southern Africa regional market



(d) Co-movement with the West African regional market

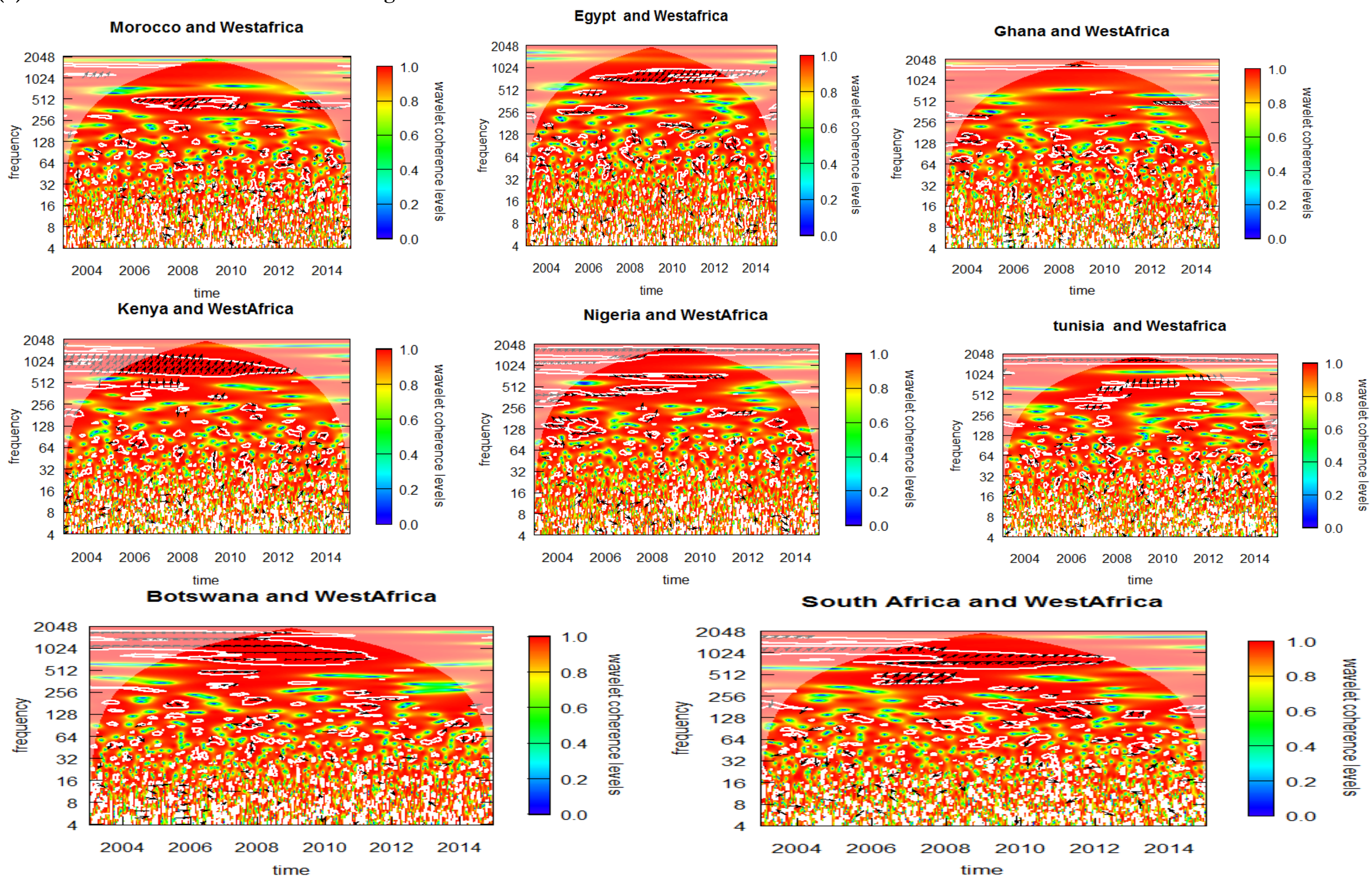


Figure *3.4a-d*. This figure shows the cross-wavelet squared coherency and phase difference plots between volatilities of individual Africa's stock markets and each of the regional stock markets from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.

In all, we find evidence of partial segmentation of African stock markets, regionally. The instances of higher regional co-movements among markets may be reflective of the degree of openness and integration, removal of some barriers to intra-regional trade, various market liberalization programmes, as well as level of macroeconomic coordination between countries and regions. Going forward however, aggressive efforts ought to be pursued in the area of harmonizing exchange rate mechanisms, and intensifying trade and other cooperation among national governments to reduce barriers to free flow of investment capital cross regions and countries.

3.3.3 Co-movements with exchange rates

Both the international trading effect model (see for example, Aggrawal, 1981; Koulakiotis *et al.,* 2015) and the portfolio balance theory (See for example Frankel, 1983; and Ho and Huang, 2015) suggest the presence of lead-lag relationships between stock markets and exchange rates. As the local currency becomes highly volatile and unpredictable, and the cost of hedging against such uncertainty surges, domestic equity markets may respond in reverse direction through increased competitiveness of local firms arising from positive trade balances and foreign currency current accounts balances – *international trading effect model*. A highly performing local bourse, on the other hand may attract foreign capital flows causing an increase in demand for domestic assets and currency; and vice versa. Increasing aggregate demand for domestic currency relative to a foreign counterpart revalues the domestic currency – *portfolio balance theory*.[39] Whilst the above theories are sound and hold in markets, it is of interest to examine the extent of volatility co-movements across the stocks and foreign exchange (FX) markets over time.

The central hypothesis to be tested is that individual country equity market volatilities may influence or are influenced by exchange rate shocks. Already, Fratzscher (2002) suggests that exchange rate volatility may play an important role in market segmentation. After establishing evidence of partial segmentation in Africa's bourses, Kodongo and Kalu (2011) infer that US dollar – and/or euro investors can diversify their portfolio holdings across Africa's equity markets without bordering about unconditional FX price risk. To test the above hypothesis, wavelet coherence and phase difference plots of volatilities of Africa's stocks and country-specific exchange rates expressed in euros and US dollars are examined for nature and degree of correlation and presence of homogeneous effects (lead-lag relationships).

[39] See also Boako *et al.,* (2016).

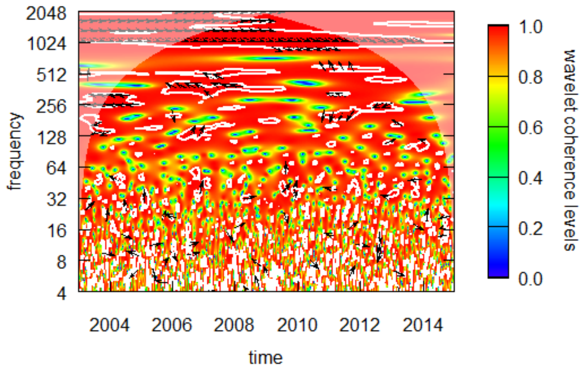
The plots are shown in Figure 3.5. Although similar to Figures 3.3 and 3.4, the red colour code spreads through the cone of influence, actual regions of significance (as measured by the contours) are scanty. Figure 3.5a for the co-movement with the US dollar shows that exchange rate volatility has sparse correlation with the volatilities of each of the stock markets in Ghana, and to some extent Nigeria. Despite this, correlations exist between the US dollar and each of the markets of Botswana, Morocco, Tunisia, Egypt, South Africa, and Kenya. Among these, both Botswana and Morocco have strong positive correlations with the US dollar at the 1024 band, whiles South Africa, Egypt, Tunisia, and Kenya exhibit strong negative relationships each with the US dollar. In the case of the latter relationships, the African markets lead the dollar.

In Figure 3.5b, all markets show relatively some noticeable, albeit scant co-movements (in some cases). The exceptions are Ghana and Botswana which appear not to show any meaningful coherencies with the Euro. In all, the relationship is negative. It is important to note that co-movements in both 3.5a and 3.5b are generally sparse, periodic, non-homogeneous, and occur at higher frequencies (shorter times).

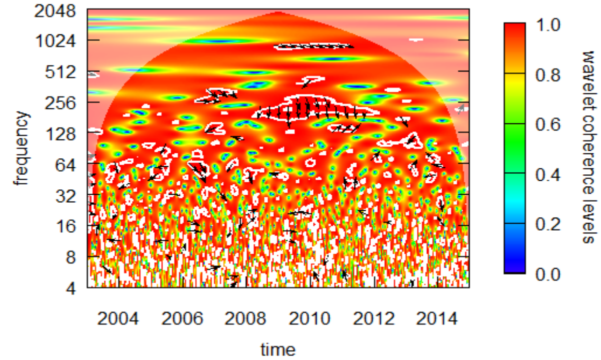
In fact, the evidence of lead-lag (negative) or positive relationships at higher frequencies (short-run fluctuations) confirms the complex dynamics of the nexus between stock market volatilities and that of exchange rates. In view of the preponderance of the generally scant and negative co- movements, we can infer that most African stock markets are moderately segmented from volatilities of the dollar and euro exchange rates, and that international investors may feel comfortable in diversifying their portfolio investments across African stocks without worrying about currency price volatility. This strategy however appears workable for investors with long-term investment horizons since coherencies are largely in the higher frequencies (shorter times).

a. Co-movement with US dollar FX

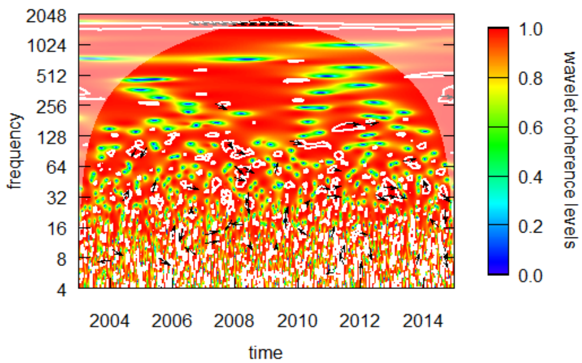
Botswana and USD



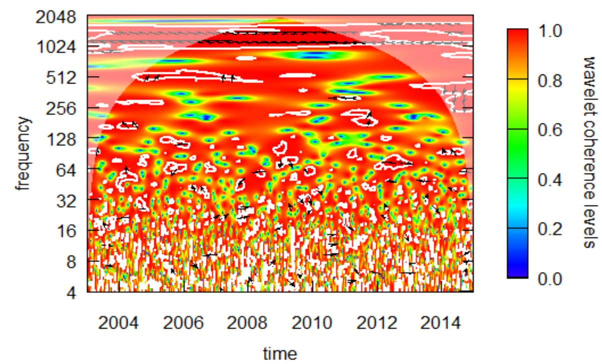
Egypt and USD



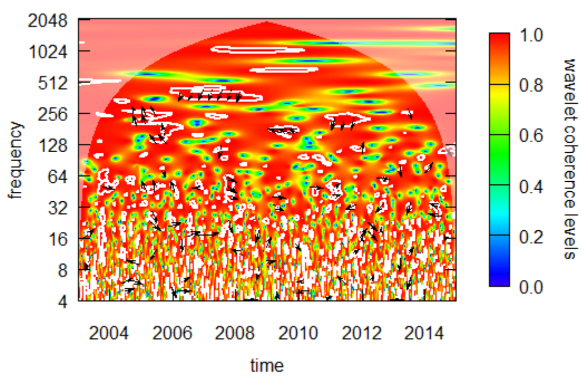
Ghana and USD



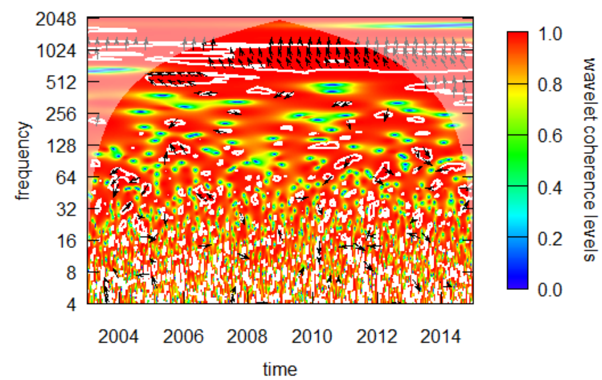
Morroco and USD



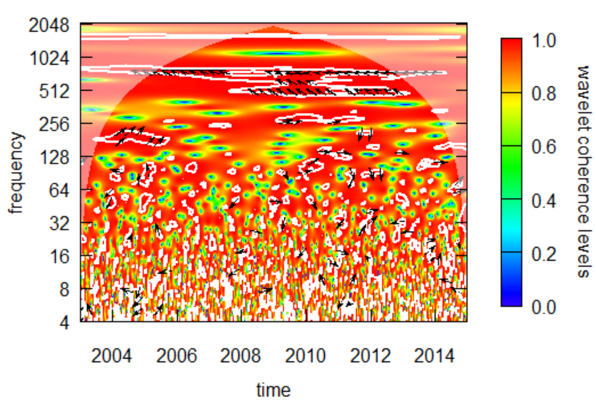
Nigeria and USD



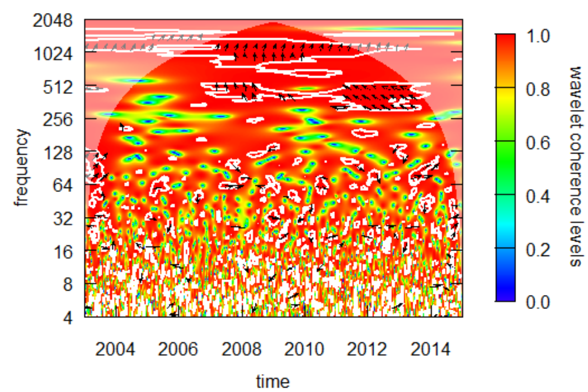
South Africa and USD



Tunisia and USD



Kenya and USD



b. Co-movement with Euro FX

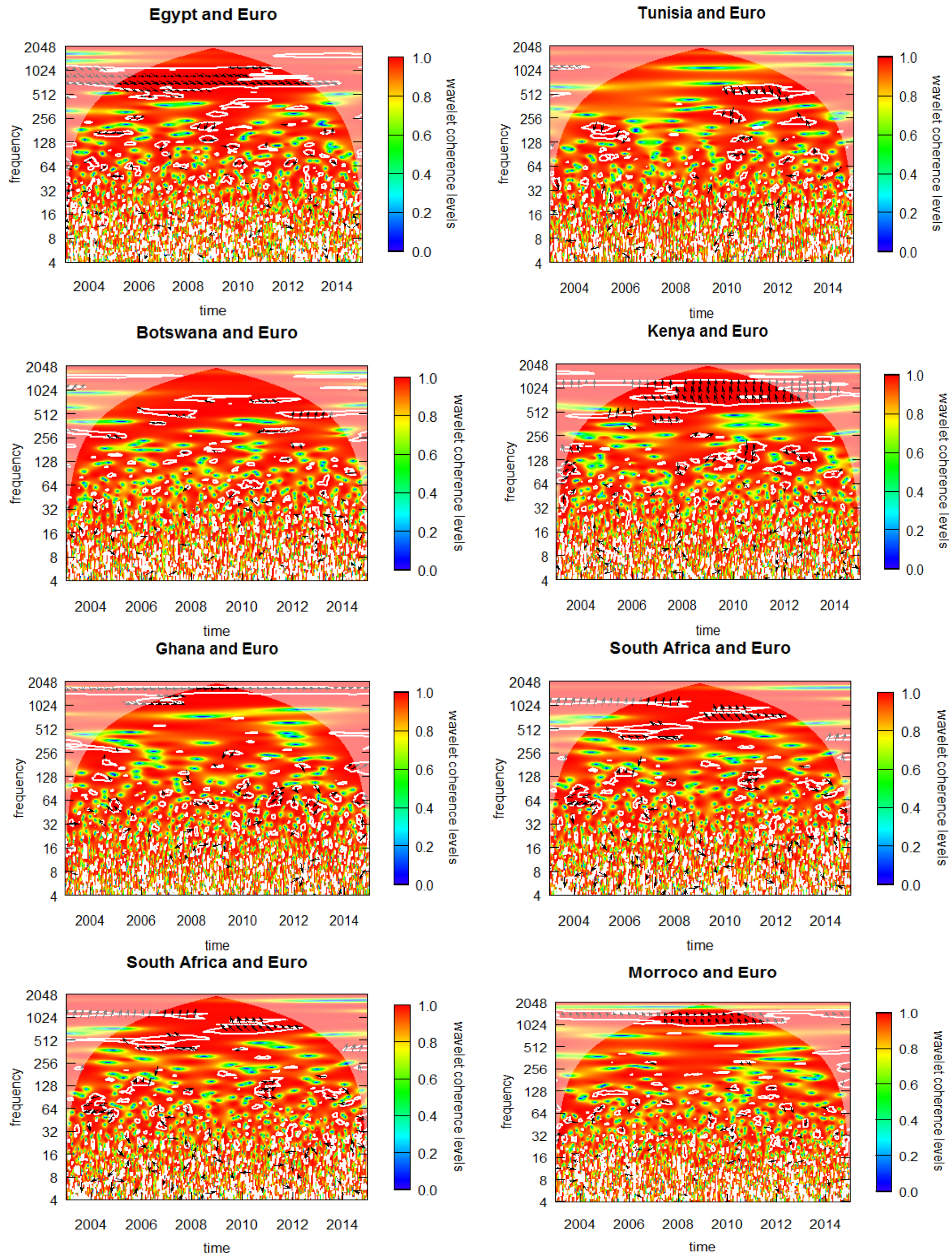


Figure 3.5a-b. This figure shows the cross-wavelet squared coherency and phase difference plots between volatilities of Africa's stock markets on one hand, and bilateral exchange rates expressed in US dollars and Euro on the other hand from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.

3.4 Conclusion

Examining regional and global co-movement of Africa's equity markets, which serves as the subject matter of this chapter, may have implications for both portfolio selection and allocation decisions of investors, as well as for policy makers in surmounting the conundrums of Africa's financial markets integration agenda and shaping policy responses towards integrated and independent financial markets. We apply the three-dimensional continuous Morlet wavelet technique to examine regional and global co-movements of African stock markets. The technique is robust to existing measures of co-movement and integration due to is localization in the frequency-time domains and ability to breakdown any ex-post variables on different frequencies to examine the subtleties of joint movements across diverse time horizons without losses in information.

Our results show evidence of stronger time-varying non-homogeneous co-movements of Africa's stocks regionally and globally at higher frequencies (shorter times). Energy concentration of markets variances is however observed to be stronger at lower frequencies. On account of the many noticeable coherencies and lead-lag relationships occurring at higher frequencies, we argue that diversification opportunities may be more practicable for investors operating in the long-term than those in the short-term.

Our findings generally support the literature on increasing co-movements among international equity markets. Also, co-movements with the global commodities index's (BCOM) around the 2007-2009 GFC period was stronger and more noticeable for most African countries (example, South Africa, Nigeria, Botswana, and Kenya) that have large scale trading in one commodity or another. Thus, these markets could not be sheltered from the contagion effects of the global commodities market shocks during the crisis. The results further show evidence of regional co-movemts of some African stock markets. The regional co-movements however, appear slow and weak post 2012. In all cases of regional co-movemnts, regional markets have shown leadership. This reinforces the need for Africa to quicken steps in fostering greater co-operations among markets and develop stronger coordinated regional markets. The findings also make it possible to infer that most African stock markets are partially segmented from volatilities of the dollar and euro exchange rates and that international investors may feel comfortable in diversifying their portfolio investments across African stocks without worrying about currency price volatility. This recommendation however appears plausible for investors with long-term investment horizons since coherencies are largely in the higher frequencies (shorter periods).

By way of extension, future studies could explore regional and international co-movements of Africa's stock markets at the firm level to examine how different firms (low, medium, or high cap) co-move with regional and international counterparts and markets. Again, the periodic nature of the identified co-movements in this paper implies that different global or regional market innovations attract varying responses from Africa's markets over time. Future studies could therefore consider investigating the reasons for such periodic relationships and the kind of business/market cycle events that characterize such co-movements.

References

AfDB, OECD, UNDP (2015). African economic outlook 2015: Regional development and spatial inclusion. http://www.google.com/url?sa=t&rct=j&q=&esrc=

Aggrawal, R., (1981). Exchange rates and stock prices: A case study of the US capital markets under floating exchange rates. *Akron Business Economic Review*, 12: 7-12.

Aguiar-Conraria L., Soares M.J., (2011). The continuous wavelet transform: A primer. *NIPE Working Paper Series* 16/2011.

Ahmed, D.A., Mmolainyane, K.K., (2014). Financial integration, capital market development and economic performance: Empirical evidence from Botswana. *Economic Modeling*, 42:1-14.

Ahmed, S., Cruz, M., Go, D.S., Maliszewska, M., Osorio-Rodarte, I., (2014). How significant is Africa's demographic dividend for its future growth and poverty reduction? *Policy Research Working Paper, No. 7134*, World Bank, Washington, DC, www.wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/2014/12/08

Alagidede, P., (2008). African stock market integration: Implications for portfolio diversification and international risk sharing. *Proceedings of the African Economic Conference* 2008, pp. 26 – 54.

Alagidede, P., (2010). Equity market integration in Africa. *African Review of Economics and Finance,* 1:88-119.

Beck, T., Fuchs, M., Uy, M., (2009). Finance in Africa: Achievements and challenges. *Policy Research Working Paper – 5020, the World Bank Africa Region Finance and Private Sector Development Department*, Auguts, 2009, pp. 1-39.

Bekaert, G., Harvey, C. R., (2014). Emerging equity markets in a globalizing world. *Available at SSRN: http://ssrn.com/abstract=2344817 or http://dx.doi.org/10.2139/ssrn.2344817*

Berben, R.-P., Jansen, W.J (2005). Co-movement in international equity markets: A sectoral view. *Journal of International Money and Finance*, 24: 835-857.

Berger, D., Pukthuanthong, K., Yang, J.J., (2011). International diversification with frontier markets. *Journal of Financial Economics,* 101: 227-242.

Boako, G., Omane-Adjapong, M., Frimpong, J.M. (2016). Stock returns and exchange rate nexus in Ghana: a Bayesian quantile regression approach. *South African Journal of Economics*, 84:149-179.

Bodenhorn, H., Cuberes, D., (2010). Financial development and city growth: Evidence from North Eastern American cities, 1790-1870. *Documents de Treball de I'IEB*, 2010/35.

Carreiri, F., Errunza, V., Hogan, K., (2007). Characterizing world market integration through time. *Journal of Financial and Quantitative Analysis*, 42: 915-940.

Chakrabarty, A., De, A., Gunasekaran, A., (2015). Investment horizon heterogeneity and wavelet: Overview and further research directions. *Physica A*, 429: 45-61.

Chang, C.,P., Lee, C.-C., (2015). Do oil spot and futures prices move together? *Energy Economics,* pp. 1-21.

Chinzara, Z., Kambadza, T.H.D., (2014). Evidence of segmentation among African equity markets. *The African Finance Journal*, 16:19-38.

Frankel, J. A. (1983). Monetary and portfolio-balance models of exchange rate determination. In J. S. Bhandari and B. H. Puntam (eds), *Economic Interdependence and Flexible Rates*. Cambridge, MA: MIT Press, Pp. xviii, 547, Index. Paper. ISBN 0-262-02177-3.

Fratzscher, M., (2002). Financial market integration in Europe: On the effects of EMU on stock markets. *International Journal of Finance and Economics*, 7:165-193.

Garham, M., Nikkinen, J., (2011). Co-movement of the Finish and international stock markets: a wavelet analysis. *European Journal of Finance*, 17:409-425.

Garham, M., Kiviaho, J., Nikkinen, J., (2012). Integration of 22 emerging stock markets: A three dimensional analysis. *Global Finance Journal*, 23:34-47.

Gorton, G., Rouwenhorst, G.K., (2006). Facts and fantasies about commodity futures. *Financial Analysts Journal*, 6(2): 47-68.

Grinstead, A., Moore, J.C., Jevrejeva, S., (2004). Application of the cross wavelet transform and Wavelet coherence to geographical time series. *Non-linear Processes in Geophysics*, 11: 561-566.

Ho, L-C., Huang, C-H., (2015). The nonlinear relationships between stock indexes and exchange rates. *Japan and the World Economy*, pp. 1-18.

IFC., (1999). The IFC Indexes: Methodology, definition, and practices. World Bank Emerging Markets Data Base. *Journal of Finance*, 55:529-564.

Kodongo, O., Kalu, O., (2011). Foreign exchange risk pricing and equity market segmentation in Africa. *Journal of Banking and Finance*, 35: 2295-2310.

Koulakiotis, A., Kiohos, A., Babalos, V., (2015). Exploring the interaction between stock price Index and exchange rates: An asymmetric threshold approach. *Applied Economics*, 47: 1273-1285.

Lee, H.S., (2004). International transmission of stock market movements: A wavelet analysis. *Applied Economics Letters*, 11:197-201.

Litse, K.J., Mupotola, M., (2014): In: Mougani, G., (2014). Challenges towards Regional financial integration and monetary coordination in the West African Monetary Zone and the East African Community. *Regional Integration Policy Paper, African Development Bank*, pp. 1-56.

Longin, F., Solnik, B., (1995). Is the correlation in international equity returns constant: 1970-1990? *Journal of International Money and Finance*, 14: 3-26.

Madaleno, M., Pinho, C., (2010). Relationship of the multiscale variability on world indices. *Review of Economics and Finance*, 20:69-92.

Madaleno, M., Pinho, C., (2012). International stock market indices co-movements: A new look. *International Journal of Finance and Economics*, 17: 89-102.

Moss, T.J., Thuotte, R., (2013). Nowhere to hide? Stock market correlation, regional diversification, and the case for investing in Africa. *Center for Global Development Working Paper* No. 316, pp.1-20.

Motelle, S., Biekpe, N., (2015). Financial integration and stability in the Southern African Development Community. *Journal of Economics and Business*, 79:110-117.

Mougani, G., (2014). Challenges towards regional financial integration and monetary coordination in the West African Monetary Zone and the East African Community. *Regional Integration Policy Paper, African Development Bank*, pp. 1-56.

Nikkinen, J., Sahlstrom, P., Vahamaa, S., (2006). Implied volatility linkages among major European currencies. *Journal of International Financial Markets, Institutions & Money*, 16:87-103.

Ntim, C.G., (2012). Why African stock markets should formally harmonize and integrate their operations. *African Review of Economics and Finance*, 4 (1): 53-72.

Ntim, C.G., Oppong, K.K., Danbolt, J., Dewotor, F., (2011). Testing the weak-form efficiency in African stock markets. *Managerial Finance*, 37(3): 195-218.

Pinho, C., Madaleno, M., (2011). Multiscale analysis of European electricity markets. Available at: www.efmaefm.org/0EF**MAM**EETINGS/.../**2011**-Braga/papers/0295.pdf. Assessed date: 20th July, 2015; pp.2-30.

Pukthuanthong, K., Roll, R., (2009). Global market integration: An alternative measure and its application. *Journal of Financial Economics*, 94: 214-232.

Roesch, A., Schmidbauer, R., (2014). WaveletComp: Computational Wavelet analysis. Rpackageversion.http://www.hsstat.com/projects/WaveletComp/WaveletComp_guided_tour.pdf

Simatele, M., (2014). Reflections on the impact of the financial crisis on sub-Saharan Africa. *Africa Growth Agenda*, 18-24.

Tiwari, A.K., Suresh, K.G., Arouri, M., Teulon, F., (2014). Causality between consumer price and producer price: Evidence from Mexico. *Economic Modeling*, 36:432-440.

Torrence, C., Compo, G.P., (1998). Practical guide to wavelet analysis. *Bulletin of American Meteorological Society*, 79:61-78.

Torrence, C., Webster, P., (1999). Interdecadal Changes in the ESNO-Monsoon System. *Journal of Climate*, 12: 2679–2690.

Vacha, I., Barunik, J., (2012). Co-movement of energy commodities Revisited: Evidence from wavelet coherence analysis. *Energy Economics*, 34:241-247.

Voronkova, S., (2004). Equity market integration in Central European emerging markets: A coin-tegration analysis with shifting-regimes. *International Review of Financial Analysis*, 13:633-647.

Zeileis, A., Kleiber, C., Kramer, W., Hornik, K., (2003). Testing and dating of structural changes in practice. *Computational Statistics and Data Analysis*, 44: 109-123.

Appendix 3.0: **Test for multiple structural shocks (changes)**

	m – change points (*change dates*)		
	***m*=1**	***m*=2**	***m*=3**
BCOM	*1006 (08:18:08)*	*1395 (04:09:10)*	*2001 (08:16:12)*
MSCI-DW	*1009 (08:21:08)*	*1405 (04:23:10)*	*2091 (12:20:12)*
MSCI-EM	*770 (12:14:06)*	*1220 (07:30:09)*	*1922 (04:26:12)*
Botswana	*997 (07:29:08)*	*1430 (05:28:10)*	***********
Egypt	*580 (01:19:06)*	*1148(04:10:09)*	*2023 (09:17:12)*
Ghana	*1075 (12:09:08)*	*1585 (01:04:11)*	*2108 (01:21:13)*
Kenya	*855 (09:04:07)*	*1244 (09:02:09)*	*1902 (03:27:12)*
Southern Africa	*832 (07:02:07)*	*1221 (07:31:09)*	*1991 (08:02:12)*
Morocco	*574 (01:02:06)*	*1141 (04:01:09)*	*2018 (09:10:12)*
Nigeria	*963 (05:15:08)*	*1352 (02/05/10)*	***********
Tunisia	*999 (07:31:08)*	*1741 (08:12:11)*	***********
North Africa	*574 (01:02:06)*	*1141 (04:01:09)*	*2091 (12:20:12)*
East Africa	*785 (4:18:07)*	*1330 (01:06:10)*	*1792 (10:24:11)*
South Africa	*832 (07:02:07)*	*1221 (07:31:09)*	*1991 (08:02:12)*
West Africa	*968 (05:28:08)*	*1357 (02:12:10)*	***********

m–change points denote the number of detected multiple shocks (change) points; and change dates gives the dating of the change points detected. The dating for the changes is of format: (month: day: year)

CHAPTER FOUR

Regionalization vs. Internationalization of African Stock Markets: Decoupling and Convergence

4. Introduction

In the last three decades efforts by various African governments and organizations/agencies to attain economic integration have not been pursued without the desire to ensure that the rather segmented financial systems in the continent are linked up together. These efforts have been greatly pursued along with changes in the financial structure and institutions on account of liberalization, innovation, and globalization (Asongu, 2012). Although some analysts believe that efforts towards Africa's economic integration agenda are snail-paced, some recordable successes have been achieved. For instance, gains have been made in the development of regional infrastructure and near elimination of intra-regional trade barriers (Mougani, 2014). These gains largely have been realized on the back of informal and formal rules/norms imposed on individual countries by respective regional and continental bodies with mandate to operationalize economic and financial sector reforms. However, because domestic financial markets remain heterogeneous despite integration and globalization, adopting a set of common rules among countries may not necessarily signify economic/financial convergence over time (Asongu, 2012). Asongu (2013) opines that Africa is largely becoming a beacon for world investment and for this dream to materialize there is the need for the continent to establish long-term financial solutions to its investments needs including regional integration and financial sector convergence.

Kawai and Motonishi (2005) suggest that measures of financial sector convergence can be categorized into three: price based measures (e.g. interest rate parity and stock markets), quality-based measures, and investment-based regulatory measures. Financial markets convergence in the framework of this chapter can be defined (in the context of price-based measures) as the harmonization and deepening of financial links through market structures to ensure an integrated financial system.[40] Such convergence of Africa's nascent markets are needful for some significant reasons: (i) to foster higher economic development through increased markets liquidity and lower cost of capital, (ii) to enhance informational efficiency, (iii) to overcome diseconomies, (iv) to condense the potential for arbitrage profits, etc – see also Furstenburg and Jean, (1989), Senbet

[40] The markets price harmonization process should however not be seen as the case of economic convergence criteria with a set of predetermined objectives.

(2009), Ntim (2012), Asongu (2012), Coudert *et al.,* (2013), among others. On the flipside, financial markets integration is noted to aid shocks contagion with consequences for markets stability. Again, markets integration may decrease the importance of the quality of securities regulation (Asongu, 2012) and make country specific factors less relevant in asset pricing (Bekaert and Harvey, 1995). It is argued that the fear of vulnerability to the above adverse effects has led to some governments' reluctance to pursue programmes aimed at enhancing markets integration (Coudert *et al.,* 2013).

Debates about emerging markets decoupling from global markets became widespread during the global financial crisis (GFC) of 2007-2009- (see Dooley and Hutchison, 2009). Despite this, empirical literature has mainly focused on contagion other than decoupling. Even that, in Africa, research on both contagion and decoupling remains extremely scanty. Meanwhile, there is a compelling reason to establish evidence or otherwise of Africa's potential decoupling from global shocks in order to provide a clearer view of whether or not its economies can offer active diversification opportunities to international investors during global markets' sell-offs.

The decoupling phenomenon holds that crashes in the global economy do not necessarily result in losses in emerging markets' stocks; and that stocks in emerging markets provide active diversification during crisis (see Gulko, 2002; Fitz-Gerald, 2010; Willet *et al.,* 2011 for the theoretical basis on the decoupling hypothesis).[41] Thus, returns from global and emerging markets stocks are not jointly normal. However, critics of the decoupling thesis contend that to believe in the existence of decoupling is nothing but suggesting that the global economy is disconnected (Fitz-Gerald, 2010). Considering the uncertainty surrounding the joint non-normality assumption, it is useful to examine whether African markets decoupled from global shocks in order to ascertain their ability to provide a risk-mitigating hedge for international investors seeking to diversify their portfolios pre-, during-, and post-crisis.[42] On the basis of the above, the aim of this chapter is to examine the extent to which regional and global markets converge with, and /or decouple from individual markets in Africa, and the influence of the 2007-2009 GFC in moderating spillover effects. The literature on stock markets convergence and decoupling has been dominated by studies on developed and some emerging markets such as the BRICS. In fact Alagidede (2008) bemoans the utter neglect of related studies in

[41] If markets are not decoupled then they are recoupled.
[42] Gulko (2002) reports that the decoupling hypothesis holds implications for diversification during financial crisis, at the time diversification are needed most.

Africa despite the fact that the continent's financial markets are relatively nascent, partially segmented (Odongo and Ojah, 2011, Ntim, 2012), less risky and have less developed operating institutional environments (Alagidede, 2008). Africa, just like any other developing region deserves particular attention in this regard due to its recent strengthening of economic links to developed countries - see Sugimoto *et al.,* (2014) and Chapter 1.

Four major contributions/outcomes are key in this chapter. First, our modeling of shock spillovers allows for the capturing of volatility transmissions in tranquil and crisis periods. This sheds light on the argument that financial markets exhibit explosive volatility during crisis that may spillover to other markets (Engle, 2004; Dungey and Gajurel, 2015).

Second, apart from distinguishing spillovers emanating from regional blocks or global markets, our CAPM analytic model allows for the examination of whether shocks from a region are as a result of some shock interceptions from global markets or due to 'own shock' (i.e. regional shocks only). It is also instructive to note that, we are able to examine separately shocks emanating from global or emerging stock markets, and shocks from the commodity markets.

Third, in similarity to this chapter, earlier global studies on convergence have applied the neoclassical income convergence hypothesis (ICH) to stock markets (see for example, Kim *et al.,* 2005, Brada *et al.,* 2005, Fung, 2009, Narayan *et al.,* 2011). Despite this, some differences exist. Of greater similarity to this chapter are Fung (2009) and Narayan *et al.,* (2011). Whilst Fung (2009) analyses the convergence of financial development (defined as private credit and quasi-money), Narayan *et al.,* (2011) examine both conditional and unconditional convergence of stock market capitalization and stocks traded. In Africa, a quick scan of the literature on stock markets convergence reveals Asongu (2012, 2013). The two papers by the author examine convergence of financial intermediary dynamics by using openness and inflation alongside stock market performance measures such as market capitalization, turn-over ratio, value traded, per capital number of listed stocks – Asongu (2012); and depth, efficiency, money, credit, activity and size – Asongu (2013). Our approach to the examination of convergence differs from all the above (i.e. global and African studies) in two distinctive quarters: (a) although Fung (2009) and Narayan *et al.,* (2011) and Asongu (2012, 2013) examine financial markets convergence, none of them considers the convergence of stock market indices; (b) apart from the differences in type of data used, the span of data used by both Asongu (2013) – from 1991 to 2009 and Narayan *et al.,* (2011) – from 1985-2008, extant studies do not adequately capture both the extreme and post periods of the 2007-2009 GFC.

Principally, we test for stock markets convergence by using daily data extended over relatively longer period (2003 to 2014); (c) to the best of our knowledge, studies on stock markets convergence (including those cited above) have employed the panel data technique with the shortfall that all markets are in transition to steady-state equilibrium in the entire sample period. Further, only the hypothesis that all markets in the sample are converging against the alternative that none is converging is actually tested, thereby excluding the possibility that some are converging whiles others are not (King and Ramlogan-Dobson, 2015) – see also Carlino and Mills (1996). Our approach of using time series analysis to test for stock markets convergence is therefore robust to existing related studies. The key strengths of this approach are that (i) it is able to analyze convergence on country-by-country basis and accommodate differences in their makeshift dynamics; and (ii) it has the strength to distinguish between several forms of convergence – see King and Ramlogan-Dobson, (2015).

Fourth, our data includes eight African stock markets (Egypt, Ghana, Tunisia, South Africa, Nigeria, Botswana, Morocco, and Kenya), which constitute the bulk of Africa's over-all total market capitalization. It is instructive to note that, of the above markets, South Africa, Egypt, and Morocco are IFC (1999) classified emerging markets. Ghana and Botswana are currently being considered for inclusion in the Morgan Stanley Capital International (MSCI) Frontier Markets Index (Berger *et al.,* 2011).[43] Thus, although African stock markets may not be significant on the global scale, the study nevertheless fills the gap in the dearth of extant literature by contributing to the literature on emerging or frontier markets. We also factor in our analysis regional markets constituted into North Africa, East Africa, West Africa, and Southern Africa; two global stock markets (MSCI-Developed World Markets and MSCI-Emerging Markets); and the Bloomberg commodities index.

4.1 The decoupling phenomenon

Across the many global financial crises, from the NASDAQ technology bubble, the Asian flu, and the great GFC of 2007-2009, just to mention a few, many international finance scholars still hold the

[43] The frontier markets classification factors the level of capital markets development, market liquidity, and investments restrictions.

view of African markets "decoupling" from various crises. At the onset of the 2007-2009 financial crisis, many were of the opinion that emerging and developing economies were insulated from the global economic turmoil. The argument behind this believe was the touted "decoupling theory", which assumes that following the crisis, the U.S. economy is no longer the driver of world economic growth but the developing and emerging market economies. Another implication of the decoupling theory is that returns of U.S (developed) equities and that of emerging markets are not jointly normal. Even though, commentaries on decoupling have largely centered on financial markets Willet *et al.,* (2011) believe that such thoughts only confirm how the concept of decoupling is widely misunderstood and misapplied. Proponents of the decoupling theory became vocal when growth in U.S began to decline in 2005 without realizable effects on growth in other regions. Markets that show signs of decoupling offer better diversification opportunities to investors when global markets like those in the U.S begin to decline. This was the situation in 2007, as more investors shifted to emerging markets as the crisis worsened.

In Africa, debates about decoupling gained grounds following the GFC. Proponents of Africa's decoupling believe that the continent's low level of integration makes it difficult to be readily affected by global shocks. However, Senbet and Gande (2009) report that during the GFC, African economies that were even weakly integrated could not be completely insulated due to contagion through the real sector. This strengthens the view that contagion drives market correlations to unity eroding any possible diversification opportunities and defeats the theoretical implication of the decoupling theory, i.e. the joint non-normality of returns.

Statistical information on African financial markets developments reveal moments of growth in tandem with performances in the global markets. Senbet and Otchere (2008) report that despite African markets' low capitalization and liquidity problems, they have performed outstandingly during the last decade in both absolute stock returns and risk-adjusted basis. During the fourth quarter of 2008, African stock markets recorded average annual dollar returns of 21.8 per cent compared to 22.97 per cent for Malaysia in Asia and 24.85 per cent for Mexico in Latin America (Senbet, 2009). However, the Morgan Stanley Capital International (MSCI) – Barra and Hartford Investments' report in 2008 on market meltdown around the globe (global stock market performance-4th quarter 2008) shows that during the highest periods of the financial crisis equity wealth declined sharply. U.S markets declined by 37 per cent, Japan 43 per cent, Latin America 38 per cent, 51 per cent in China; and in Europe 38.5 per cent. Correspondingly, the well-integrated African markets were not invulnerable, as they recorded the following declines: Egypt 55 per cent, Mauritius 49 per cent, Nigeria 59 per cent, South Africa 33 per cent, and Kenya 31 per cent. From the above discourses, it is unclear whether or not African markets can be said to have decoupled from global markets sell-offs.

4.2 Research design

To examine Africa's stock markets convergence/decoupling regionally and globally, the study adopts a three-stage methodological approach. First, we dwell on some preliminary tests using descriptive statistics, logarithmic time plots, and correlation analysis to examine the basic features as well as evolution of joint movements of the series over time. Second, the Neoclassical Income Convergence Hypothesis (ICH) is used to determine convergence over the entire sample of the data. The approach is able to identify the presence of convergence as well as the nature of convergence - *absolute or deterministic*. The ICH technique is executed using unit roots test to determine the order of integration of a certain derived differential series from two individual series whose convergence are under examination. Third, do markets linkages convey any implications for shocks spill-over? We try to address this question by applying a step-wise ordinary least squares estimation technique within a standard asset pricing model that allows for spillovers pre-, during-, and post- the GFC and model convergence (decoupling) as the propagation (no propagation) of shocks. This estimation technique will take into account the time-varying nature of the decoupling process.

4.2.1 The 'market convergence hypothesis' - MCH

Inspired by Solow's (1956) neoclassical growth model, the income convergence hypothesis (ICH) has seen several applications in growth empirics (example, Baumol, 1986; Benard and Durlauf, 1995; Brada *et al.,* 2005; Fung, 2009; King and Ramlogan-Dobson, 2015). The ICH believes in the gradual tendencies for international differences in per capita income to diminish over time. Principally, two main concerns arise in the application of the ICH on growth related studies (Narayan *et al.,* 2011): whether or not low growth economies converge to high growth economies; and the speed of convergence, if any – see also Barro and Sala-i-Martin (1992).

In this chapter, we rely on the convergence hypothesis in the equity market framework to estimate the convergence of African stocks globally and regionally. We term this the "market convergence hypothesis" (MCH). Although, the convergence hypothesis has largely been applied to economic growth, we are not the first to apply it to financial markets (see Kim *et al.,* 2005, Narayan *et al.,* 2011, and the papers cited therein) although differences exist. Within, the equity market set-up, studies that show some marginal similarities to ours are Narayan *et al.,* (2011), and Asongu (2013). The main differences here are the nature and type of data sets used as well as the empirical techniques employed to test for the convergence. Both studies (as earlier mentioned) have weaknesses methodologically and analytically. As noted by Benard and Durlauf (1995) and King and Ramlogan-Dobson, (2015), applying the ICH to cross-sectional and panel data has many shortfalls. This is true since the two approaches assume that all markets are in transition to steady-state equilibrium in the entire sample period. Again, they are only able to test the hypothesis that all markets in the sample are converging against the alternative that none is converging, thereby excluding the possibility that some are converging whiles others are not (King and Ramlogan-Dobson, 2015) – see also Carlino and Mills (1996).

On the basis of the above, we adopt the time series approach akin to King and Ramlogan-Dobson (2015). The key strengths of this approach are that: first, it is able to analyze convergence on country-by-country basis and accommodate differences in their makeshift dynamics; and secondly, it has the strength to distinguish between several forms of convergence.

Akin to King and Ramlogan-Dobson (2015), we specify a model to relate stock indices in Africa, corresponding regional indices, and that of global markets (be it stocks or commodities). For this, the log difference of the index series of an African country's stock (*i*) and that of a particular region or global market (*j*) is computed as:

$$yd = \ln S_i - \ln E_i \qquad [4.0]$$

where S = stock price index in Africa, and E = regional or global market (and E can be stock or commodity price/index).

If yd is observed to be integrated of order *I(1)* or possess unit roots, it will be considered that there is no convergence between the two indices paths. This would mean a random walk process with no stable and systematic linkage between the two markets. On the other hand, a yd integrated of *I(0)* would mean that shocks to yd do not persist perpetually making the index differential between the two markets (Africa and regional/global) follow a stochastic trend asymptotically. This long-run mean reversion of the series could be construed as some evidence of convergence between the two markets.

The nature or form of convergence is dependent on the characteristics of the deterministic trend of yd. If the long-rum equilibrium index path of i and j follow the same trend, the convergence between the two can be described as *absolute*. In this case, the forecasts of yd will approach zero as the forecast horizon inches infinity (Benard and Durlauf, 1995). Thus:

$$\lim_{q \to \infty} E\left(yd_{t+q} \mid \Omega_t\right) = 0 \qquad [4.1]$$

where Ω_t is the information set at time t.

Equation [4.1] renders yd zero-mean stationary. A non-zero mean stationary process of yd yields a *deterministic convergence (*Li and Papell, 1999). In this case, the returns/prices of the two markets are said to be in a steady-state, however, structural differences between them denote a persistent difference between their price/return paths (King and Ramlogan-Dobson, 2015). In both the absolute and deterministic convergence, all shocks to yd are assumed to be transient. The inference of this assumption is challengeable however, in the sense that if it took market i to reach a steady-state level, the transitory phase may contribute to a non-zero mean of yd even if the convergence at the steady state was absolute (Benard and Durlauf, 1995) thereby compromising any inference drawn.

4.2.2 Econometric approach to the MCH: BTP spectral density test

King and Ramlogan-Dobson (2015) used the Fourier Lagrange Multiplier (LM) unit roots test to estimate the income convergence of African economies. However, we apply the Bartlett, Tukey, and Parzen (BTP) spectral density unit roots test as described in Pesaran and Pesaran (2009) to analyze the convergence of African stock markets – see also Chatfiled (2003) and Priestley (1981). The spectral analysis allows for the examination of the time series properties in the frequency domain.

For a univariate covariance stationary process $\{yd_t, t = -\infty, ..., \infty\}$ with a mean $E(yd_t) = \mu$, the *kth* auto-covariance function can be expressed as:

$$E(yd_t - \mu)(yd_{t-k} - \mu) = \gamma_k = \gamma_{-k}, \qquad k = 0,1,2,...$$

In the spectral analysis, the central motive is to determine the significance of cycles of different frequencies in accounting for the behaviour of yd_t (Pesaran and Pesaran, 2009).[44] Supposing that auto-covariances are absolutely summable $\left(\sum_{k=0}^{\infty}\gamma_k \text{ is finite}\right)$, the population spectrum can be written as:

$$f(\omega) = \frac{1}{\pi}\left\{\gamma_0 + 2\sum_{k=1}^{\infty}\gamma_k \cos(\omega k)\right\}, \quad 0 \le \omega < \pi \qquad [4.2]$$

- If yd_t is a white noise process $\left(\gamma_0 = \sigma^2 \text{ and } \gamma_k = 0 \text{ for } k \neq 0\right)$, then $f(\omega)$ is flat at σ^2/π for all $\omega \in [0, \pi]$.
- If yd_t is a stationary $AR(1)$ process, $x_t = \mu + \phi yd_{t-1} + \varepsilon_t$ with $|\phi| < 1$ and ε_t being a white noise process, then $f(\omega)$ is monotonically decreasing in ω for $\phi > 0$, and a monotonically increasing function of ω for $\phi < 0$.
- If yd_t is a stationary $MA(1)$ process, $yd_t = \mu + \varepsilon_t + \theta\varepsilon_{t-1}$ with $|\theta| < 1$ and ε_t being a white noise process, then $f(\omega)$ is monotonically decreasing (increasing) in ω for $\theta > 0$ (for $\theta < 0$).

The sample spectral density function may be estimated by:

$$f(\omega) = \frac{1}{\pi}\left\{\tilde{\gamma}_0 + 2\sum_{k=1}^{\infty}\tilde{\gamma}_k \cos(\omega k)\right\}, \; 0 \le \omega < \pi \qquad [4.2.1]$$

where $\tilde{\gamma}_k$ is the sample auto-covariance obtained by:

$$\tilde{\gamma}_k = n^{-1}\sum_{t=k+1}^{\infty}\left(yd_t - y\hat{d}\right)\left(yd_{t-k} - y\hat{d}\right), \text{ for } k = 0,1,...,n-1$$

and $y\hat{d}$ is the sample mean.

Because, the sample spectral density estimator is not consistent (see also Pesaran and Pesaran, 2009), a non-parametric kernel estimate of the population spectrum can be obtained as:

[44] Any covariance stationary process has both a time-domain and a frequency-domain representation, and any feature of the data that can be described by any one representation can equally be described by the other.

$$f\left(\omega_j\right)=\sum_{i=-m}^{m}\lambda\left(\omega_{j+i},\omega_j\right)\hat{f}\left(\omega_{j+1}\right) \qquad [4.2.2]$$

where $\omega_j = j\pi / m,$ and m is a bandwidth parameter showing the number of frequencies used in estimating the population spectrum. The kernel determines the weight to be accorded to each frequency. The scaled standardized version of the kernel can be obtained by equation [4.2.3] with their estimated standard errors given by Bartlett, Tukey, and Parzen lag windows at the frequencies $\omega_j = j\pi / m,\ j = 0,1,2,...,m$. Each of the frequencies are associated with the $period = 2\pi / \omega_j = \frac{2m}{j},\ j = 0,1,2,...,m$.

$$\hat{f}_*\left(\omega_j\right)=1+2\sum_{k=1}^{m}\lambda_k\left(\hat{\gamma}_k / \hat{\gamma}_0\right)\cos\left(\omega_j k\right) \qquad [4.2.3]$$

where λ_k a set of weights is called the 'lag window'. The estimates of $\hat{f}_*\left(\omega_j\right),\ j=0,1,\ldots,m$ are obtained for the following lag windows:

$$Bartlett\,window \qquad \lambda_k = 1-k/m, \qquad 0\le k\le m$$

$$Tukey\ window \qquad \lambda_k = \frac{1}{2}\left\{1+\cos\left(\pi k/m\right)\right\}, \qquad 0\le k\le m$$

$$Parzen\ window \qquad \lambda_k = \begin{Bmatrix} 1-6\left(k/m\right)^2+6\left(k/m\right)^3, & 0\le k\le \frac{m}{2} \\ 2\left(1-k/m\right)^3, & \frac{m}{2}\le k\le m \end{Bmatrix}$$

m is by default set equal to $2\sqrt{n}.$

Standard errors for the estimates of the standardized spectrum are computed as given by equation [4.2.4] below.

$$\begin{aligned} S\hat{e}\left(\hat{f}_*\left(\omega_j\right)\right) &= \sqrt{\frac{2}{v}}\,\hat{f}_*\left(\omega_j\right), \qquad for\ \ j=1,2,\ldots,m-1 \\ &= \sqrt{\frac{4}{v}}\,\hat{f}_*\left(\omega_j\right), \qquad for\ \ j=0,m \end{aligned} \qquad [4.2.4]$$

where $v = 2n / \sum_{k=-m}^{m} \left(\lambda_k^2\right)$. For the three different windows, *v* is given by:

$$\begin{array}{ll} \textit{Bartlett window} & v = 3n/m \\ \textit{Tukey window} & v = 8n/3m \\ \textit{Parzen window} & v = 3.71n/m \end{array}$$

The long-run properties of the series are given by the value of the standardized spectrum at zero frequency, by which the spectrum of the unit root process is unbounded. A higher value indicates a greater persistence of the effects of deviations of yd_t from its trend. *As a rule, a non-stationary (unit root) process of* yd *would have a spectral density dominated by the value of the spectrum at the zero frequency which drops dramatically immediately thereafter, hiding possible peaks at higher frequencies. Again, at the zero frequency, the value of the scaled spectrum determines the long-run variance of the series considered as a measure of persistence of shocks to a market* (Cochrane, 1988).

4.2.3 Modeling decoupling and the implications for shocks spillover

4.2.3.1 The empirical framework

Using a standard CAPM framework[45], we argue that the rather partial segmentation of Africa's financial markets from global and regional counterparts may lead to their decoupling from shocks during crisis. Intuitively, if financial markets are purely segmented then there should be less common risk factors and long-term delimitations to international diversification opportunities. Thus, the absence of decoupling (recoupling) would imply the propagation (no propagation) of shocks or spillover effects. The advantage of the underlying CAPM approach in this chapter is that it does not require an exhaustive and mutually exclusive list of data, but with the disadvantage that the exact source of the spillover effects in terms of observed variables is not known (see also, Dungey and Gajurel, 2015).

Let $E(r_{it})$ be the expected return for an African stock market *i* at time *t*. In the framework of the CAPM, a standard representation of market *i's* expected return can be specified as:

$$E(r_{it}) = \lambda_{0,1} + \lambda_{1,1} \int_t^{global/regional} + \mu_{i,t}\,, \qquad [4.3]$$

[45] The approach, to some extent, is similar in concept to that used by Dungey and Gajurel (2015).

where $\int^{global/regional}$ denote global/regional or common shock and can be proxied by the return on the global/regional market; and $\lambda_{1,i}$ refers to the global/regional (benchmark portfolio) market risk exposure of African market *i*. The model removes the common global/regional effects from individual index returns (see also, Dungey and Gajurel, 2015). Equation (4.3) may apply in the international setting for both highly integrated and segmented markets.

We estimate the possibility of global or regional shocks spill-over to Africa's financial markets by analyzing if African stock markets react differently to shocks emanating from its own region or another, or a global market. The estimation is done in a step-wise OLS framework that takes into account the time-varying nature of shocks transmission and responses. This step-wise procedure is designed to capture the pre-, during-, and post-periods of the 2007-2009 global financial crisis.

We begin the analysis by regressing each market's returns (domestic, regional, or global) on a constant in order to be debased (see also Coudert *et al.,* 2013), as shown in equation (5.3.1). Thus,

$$r_t^q = \psi + \varepsilon_t^q \qquad [4.3.1]$$

where *r* is return, *q* is market (can be domestic, regional, or global), ψ is a constant, and ε^q captures the shocks of the particular market.[46] A second phase of Equation (4.3.1) is obtained in Equation (4.3.2) by regressing the returns of the regional market on both a constant and the returns of the global market. The residual obtained will then represent shocks on the regional market emanating from the interactive effects of the global and regional markets. Our objective for including this in the model is to determine separately, whether shocks from the regional market to each domestic African market is 'own shock' or shock intercepted from global markets. The model will also help us to ascertain whether the regional markets are just 'receivers' or 'transmitters' of global shocks (see details in sub-section 5.4.4). Equation (4.3.2) is thus specified as:

$$r_t^R = \psi + r_t^G + \varepsilon_t^{R*} \qquad [4.3.2]$$

[46] For instance shocks of a domestic market will be ε^d , etc.

where, R and G are regional and global markets respectively. ε^{R*} is shocks of R from G, and all others are as previously defined.

The estimable econometric models for equations (4.3.1) and (4.3.2) will respectively be equations (4.3.3) and (5.3.4). In both equations, we restrict the coefficient of each other market's shocks for brevity of exposition.

$$\varepsilon_t^d = \theta_i(\varepsilon^{R_i})_t + \gamma_i\left(\varepsilon^{G_i}\right)_t + \mu_t \qquad [4.3.3]$$

$$\mu_t \sim iid\ (0,\ \delta^2) \text{ and } i = 1,2,3,\ldots,T$$

where, d is domestic market, θ is coefficient of the regional shocks, γ is coefficient of global shocks, η is the residual of the regression model and T is the total number of regional or global markets whose shocks are considered. Again,

$$\varepsilon_t^d = \phi_i\left(\varepsilon^{R*}\right)_t + \mu_t \qquad [4.3.4]$$

$$\mu_t \sim iid\ (0,\ \delta^2) \text{ and } i = 1,2,3,\ldots,T$$

and ϕ is the coefficient. All others are as previously defined.

The structure of equations (4.3.3 and 4.3.4) assume that shocks from African stocks do not spillover to developed or global markets which rules out any symmetric or feedback effect. The evidence is limited in support of a transmission mechanism in which fluctuations in developing markets' indices lead to shocks spillover to global markets. Empirically, Sugimoto *et al.,* (2014) report that the degree of feedback spillovers from aggregate African markets to other financial markets are limited.

4.3 Data and preliminary analysis

The data sets are of daily periodicity and span the period 3rd January 2003 to 29th December, 2014. All data are gleaned from DataStream except the commodities market index which is from Bloomberg. To avoid the effects of asynchronous trading in the datasets, the close-to-close method (see also Brooks and Persand, 2001 and the references therein) is applied. The method (i.e. close-to-close) is executed by eliminating observations for all markets if the price index for a given market is not available for a certain date. Thus, we limit our sample to only days for which we have observations for all markets. The data are analyzed either in their volatilities of returns (based on absolute returns computed as the log difference between daily prices or indices) or log-levels depending on which estimation technique is executed – volatilities of returns for spill-over effects and log-levels for convergence. The sample consists of data of stock indices of eight African markets: Ghana, Nigeria, South Africa, Botswana, Morocco, Tunisia, Egypt, and Kenya.[47] The choice of these markets is based on data availability and their relative verve in the continent. Put together, the selected markets constitute the largest markets and could therefore proxy for stock markets movements in Africa.

Additionally, prices of Morgan Stanley Capital International index (MSCI), which is comprised of developed world markets (hereafter referred to as MSCI developed markets index: (MSCI-DW)), MSCI emerging markets (MSCI-EM) index, and Bloomberg Commodities (BCOM) index are included in the sample. The inclusion of the commodity index is borne out of three reasons: (a) given the recent history of commodities, fund managers around the world are eager to find actual assets that offer diversification opportunities that they failed to find in commodities since the beginning of the financialization of commodities, (b) because commodities failed to provide decorrelation during the 2007-2009 crisis, the intuition is that African stocks may be suitable candidates given their potential decoupling from other markets, (c) Again, African economies remain major global producers and consumers of commodities.[48] Price changes in the commodity markets could therefore hold significant implications for the choices and selection of alternative asset classes by both local and international investors. To overcome exchange rate noise, all data are expressed in U.S dollars.

In order to examine regional spillovers, all African equity markets with available and reliable data during the sample period are aggregated into four: East Africa, West Africa, Southern Africa, and North Africa regional stock price/indices (based on market or value-weighted average prices)

[47] All eight (8) markets sampled are open to international portfolio investment despite disparities in the level of openness.

[48] Among other things, most African countries are major producers of global commodities. For instance, Cote d'Ivoire, Ghana, Nigeria, and Cameroon are among the top 5 world produces of Cocoa, with Cote d'Ivoire being *the* leader; South Africa is among the first five gold producers in the world; four African countries (namely, Algeria, Angola, Libya, and Nigeria) are part of the twelve-member OPEC group.

constructed from individual markets indices based on a specific geographic distribution.[49] Regional indices are computer in same manner as in Equation 3.5 of Chapter three.

The empirical analysis begins with a test for the stationarity properties of all variables. Given that the spectral density test for the MCH relies on the stationarity assumption, it is important to establish the unit root properties of the series to avoid any biased inferences. We thus check the stationarity property of the variables by using the Augmented Dickey-Fuller (ADF) and Zivot and Andrews – ZA (1992) tests.[50] The null hypothesis of both the ADF and ZA tests is that the series contains unit roots against the alternative that the series is stationary. The inclusion of the ZA test is to help us overcome possible challenges in estimating unit root properties when the data contains possible breaks.[51] This is relevant because financial time series data are usually prone to high institutional changes such as financial shocks and market liberalizations which may lead to structural breaks in the data. Using the ADF test can be problematic when the sample period includes such major happenings (such as commodity shocks or stock market crashes). The stationarity test is useful because financial time-series data are usually characterized by problems of heteroscedasticity and therefore ensuring that the series follows a white-noise process is usually good to avoid bias estimates and wrong inferences.

The ADF models for testing unit roots in the presence of a random walk with a drift and a stochastic trend are specified as:

$$\Delta Y_t = \beta_0 + \beta_1 Y_{t-1} + \sum_{s=1}^{k} \gamma_s (\Delta Y)_{t-s} + u_t \qquad [4.4]$$

$$\Delta Y_t = \alpha t + \beta_1 Y_{t-1} + \sum_{s=1}^{k} \gamma_s (\Delta Y)_{t-s} + u_t \qquad [4.4.1]$$

where, $\left(\beta_1 Y_{t-1} + \sum_{s=1}^{k} \gamma_s (\Delta Y)_{t-s} \right)$ represent the augmented portion of the ADF test; β_0 is the intercept; t denotes the time trend and $\Delta Y_t = Y_t - Y_{t-1}$. A null hypothesis of a unit root, formulated as: $H_0 : \beta_1 = 0$, is tested under the ADF test.

---

49 Thus, the term 'regional market' should not be taken as a representation of a physical structure/market but a value-weighted price/index aggregate of all represented individual markets in the region.
50 See Zivot and Andrews (1992) and Boako *et al.,* (2016) for some specifications.
51 It must however be stated that the intent is not to detect the presence of (multiple) structural breaks for further empirical analysis.

Similarly, the ZA test is formulated given a change in the intercept, trend or both as:

$$\Delta Y_t = K + \alpha Y_{t-1} + \beta_t + \theta DU1_t + \sum_{s=1}^{k} d_s (\Delta Y)_{t-s} + u_t \tag{4.4.2}$$

$$\Delta Y_t = \alpha Y_{t-1} + \beta_t + \theta DU1_t + \gamma_1 DT1_t + \sum_{s=1}^{k} d_s (\Delta Y)_{t-s} + u_t \tag{4.4.3}$$

$$\Delta Y_t = K + \alpha Y_{t-1} + \beta_t + \theta DU1_t + \gamma_1 DT1_t + \sum_{s=1}^{k} d_s (\Delta Y)_{t-s} + u_t \tag{4.4.4}$$

where, ΔY_t represent a first difference operator $\left(\Delta Y_t = Y_t - Y_{t-1}\right)$; and u_t is the uncorrelated random error term. The dummies in the ZA test equations are expressed as: $DU1_t = 1$ and $DT1_t = t - TB1$ given that $t > TB1$ or 0 otherwise; and $1 < TB1 < T$; where T is taken as the sample size of the series and represents the time period where the structural break actually hits.

Results from Table 4.0 for the unit root tests show that all log observed and differenced series are non-stationary (stationary) at the levels (first difference). Thus, the taking of logs does not bias the spectral unit roots results.

Table 4.1 shows results of descriptive statistics of all series across sub-samples. Panels A, B, and C show that the daily mean returns and standard deviations (SDs) of the entire sample are higher in the crisis period than the two non-crisis periods. Averagely, daily mean returns (SDs) are 0.64% (0.62%) for Panel A; 1.37% (1.36%) for Panel B; and 0.71% (0.71%) for Panel C. The higher mean returns and SDs (our crude measure of risk) in Panel B may be attributed to the effects of the GFC. In all, the effects were higher for the global markets than the individual and regional markets in Africa. All the series exhibit positive skewness and depict excess kurtosis across samples. Thus, the probability distributions are skewed to the right and have leptokurtic behaviour with fat tails than a corresponding normal distribution. These signs fail to accept the assumptions of normality of the series, which is corroborated by the high significance of the JB test for normality. A robustness examination of the descriptive features for the full sample period using both returns and log series (though not shown for brevity of exposition) confirms the above results, except that individual African markets display both positive and negative skewness with the log index series. Bekaert and Harvey (2014) explains that individual emerging markets are generally positively skewed, however growth experiences appear country-specific, whereas some of the downside moves are common across countries, causing negative skewness at the index level.

Table 4.0: Unit root test

	ADF				ZA			
	Log observed series		***Diff. series***		***Log observed series***		***Diff. series***	
	Const.	**Trend**	Const.	Trend	**Const.**	**Trend**	Const.	Trend
African Stock Markets								
Botswana	-2.01	-1.41	-50.37*	-50.40*	-2.54	-2.63	-50.71*	-50.42*
Egypt	-3.12	-2.14	-46.57*	-46.67*	-3.79	-3.85	-46.86*	-46.78*
Ghana	-1.88	-1.72	-47.43*	-47.44*	-2.70	-2.36	-47.93*	-47.64*
Kenya	-2.12	-2.71	-38.39*	-38.44*	-3.01	-3.82	-47.32*	-47.01*
Morocco	-0.98	-2.49	-17.28*	-17.30*	-3.24	-3.70	-54.66*	-54.66*
Nigeria	-2.08	-1.84	-36.84*	-36.88*	-2.73	-1.79	-37.12*	-36.98*
South Africa	-2.24	-2.26	-49.79*	-49.81*	-3.12	-3.34	-49.98*	-49.92*
Tunisia	-2.07	-0.42	-31.37*	-31.47*	-2.13	-3.37	-45.31*	-45.16*
Global Markets								
BCOM	-1.54	-2.18	-53.01*	-53.05*	-3.22	-2.61	-53.23*	-53.06*
MSCI-DW	-1.67	-1.87	-36.81*	-36.80*	-3.23	-2.27	-46.16*	-45.93*
MSCI-EM	-1.57	-2.09	-41.84*	-41.89*	-2.61	-2.44	-42.10*	-41.90*
Regional Markets								
East Africa	-2.04	-2.68	-50.29*	-50.29*	-4.13	-2.72	-50.36*	-50.32*
North Africa	-2.07	-1.69	-48.30*	-48.32*	-3.01	-2.66	-48.44*	-48.36*
Southern Africa	-2.52	-2.19	-51.07*	-51.10*	-3.06	-3.26	-51.27*	-51.13*
West Africa	-2.35	-1.85	-37.18*	-37.23*	-2.85	-1.88	-37.58*	-37.56*

Note: *critical values of ADF with Constant – 1% (-3.43), 5%(-2.86), 10%(-2.57) and Trend – 1% (-3.96), 5% (-3.41); 10%(-3.13); ZA with Constant – 1%(-5.34), 5%(-4.80), 10%(-4.58) and Trend – 1%(-4.93), 5%(-4.42), 10%(-4.11). "*, **, ***" – denote statistical significance at the 1%, 5%, and 10% levels respectively for both ADF and ZA. Diff means difference.*

In Figure 4.0, volatility plots of all series across the entire sample are shown, to observe common stochastic trends. The figure gives some indication of general volatility clustering of the series below 0.025 interspersed with high volatility spikes across the distribution. In several instances, the spikes are highly noticeable between 2008 to 2009.

4.4. Empirical results and discussion

4.4.1 Results of the 'Market Convergence Hypothesis – MCH'

As indicated in sub-section 4.2.2, all three spectral density unit root test (i.e. Bartlett, Parzen, and Tukey) are employed to determine the presence and nature of convergence. We estimate the spectral analysis of *yd* by first regressing *yd* on a constant term and a time trend. Spectrum plots of the residual from the regression of *yd* (*resyd*) on a linear trend are then estimated with the default window (bandwidth) size value of $2\sqrt{n}$ where *n* is the number of observations. *Appendix 4A* shows plots of the estimated standardized spectral density function of all '*resyd*' using the Bartlett, Tukey, and Parzen (BTP) lag windows.

The results (see *Appendix 4A*) shows that the Bartlett, Tukey, and Parzen tests reject the stationarity hypothesis since the spectral densities are dominated by the value of the spectrum at the zero frequency, and drops dramatically thereafter – hiding possible peaks at higher frequencies. Thus, the contribution of the lowest frequency to the variance of each *yd* is much larger than the contributions of other frequencies. Despite this, the values of the scaled spectra at the zero frequencies differ from markets to markets (albeit marginal), suggesting that important differences exist on how individual African stock markets respond to shocks emanating from the global and regional markets. In general, the spectral analysis provides evidence that in the entire distribution of the series, African stock markets diverge from the global and regional markets under consideration.

4.4.2 Analyzing decoupling and spill-over effects

On account of the detected multiple structural breaks of same series in Chapter three (see *Appendix 3A*), and the fact that the number and exact dates of the breaks are not the same, selecting a particular breakpoint date for inclusion in the empirical model may be difficult. For this reason, we use ordinary least squares (OLS) regression to examine the effects of the detected structural breaks on the association between the individual regional/global market returns and each of the domestic markets in Africa (see also Boako *et al.,* 2016). This is to help us decide on discounting the effects of the breaks or to include them in our model. To do this, dummy variables taking the vales *0(1)* for periods in the sample data - regional/global markets, before and after the break dates (at the break dates) are created.[52] Results of the OLS estimation for break effects are reported in *Appendix 4B*. We observe from the results that the breaks could not substantially influence the connectedness between each domestic stock market on one hand, and each of the regional/global markets on the other hand. As a result, we decline the factoring of the structural breaks in modeling decoupling/recoupling and their implications for shocks spillover.

[52] Dummies are created for only the regional and global markets but not the individual domestic markets.

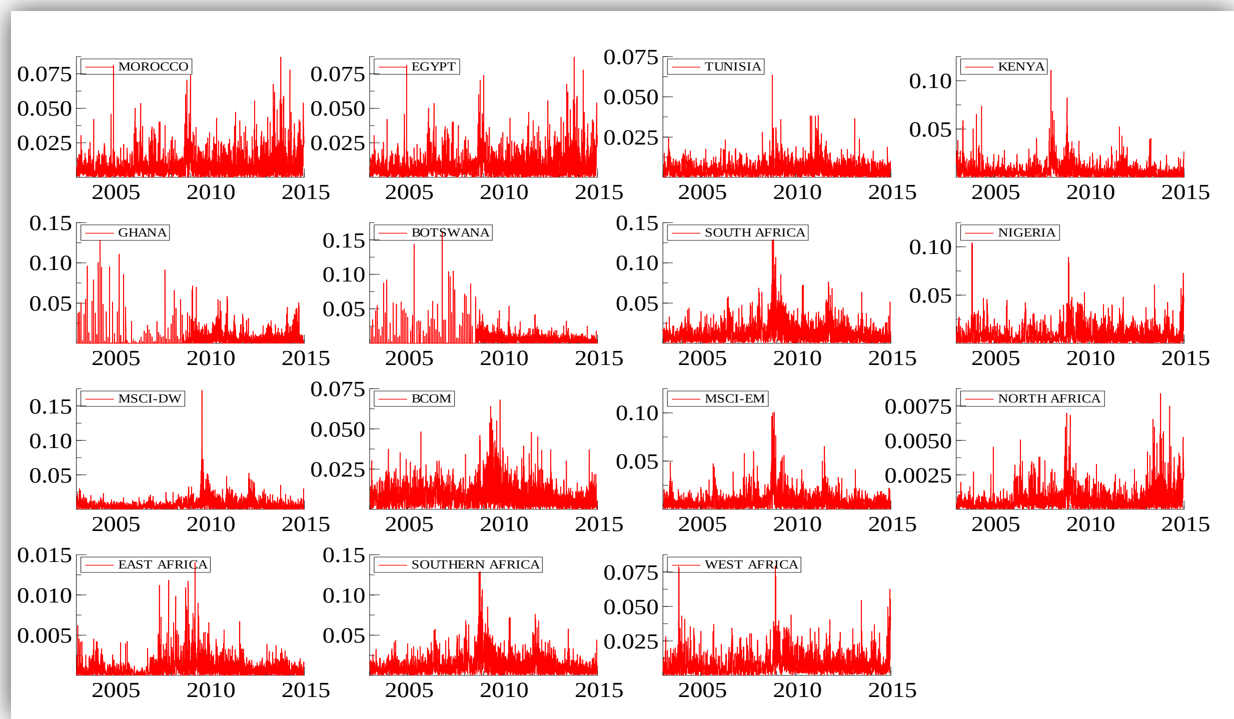


Figure 4.0: Plots of volatilities of returns

Despite this, because the pricing of risk or spillovers may be masked by time-variation we elect to model decoupling around the 2007-2009 global financial crisis (GFC) with pre-determined sample periods, in line with the literature. Thus, we disaggregate the sample into pre-, during-, and post-crisis periods. Akin to Lean and Nguyen (2014), we focus on the acute phase of the crisis, starting from the period of the bankruptcy of Lehman Brothers in mid-September, 2008 until end of May, 2009, where the G20 started cutting interest rates, various fiscal stimuli, and pursuing quantitative easing policies in an attempt to avoid the recession becoming a slump. And the end-point is consistent with the end of the recession in the US – see also Dungey and Gajurel (2015). We model decoupling/recoupling around this period because it represents the era of shocks intensification and also characterized by the failure of a large number of global financial institutions, government bail-out interventions, liquidity support and capital injections, deposit guarantees, and severe contraction in the real economy. For most emerging/developing markets, propagation of shocks are more likely to be felt at the 'acute or second' phase than the 'turmoil or first' phase of the crisis. The disaggregated data then comprise (a) a pre-crisis period from 3rd January, 2003 to September 14, 2008; (b) a crisis-period (during crisis) spanning 15th September, 2008 to 30th May, 2009; and (c) a post-crisis period from 1st June, 2009 to 29th December, 2014.

Table 4.1: Summary statistics of volatilities of returns

	Mean (%)	Std. (%)	Skew.	Kurt.	JB @ 1%	Min.	Max.
Panel A: Pre-crisis period – 3rd January, 2003 to 14th September, 2008							
Botswana	0.286	1.317	6.460	53.938	117830.6	0.000	0.160
Egypt	1.166	1.431	2.033	8.397	1948.1	0.000	0.093
Ghana	0.208	1.114	7.127	59.503	144883.9	0.000	0.128
Kenya	0.756	0.913	4.026	30.091	34080.7	0.000	0.111
Morocco	0.774	0.779	2.711	15.836	8284.7	0.000	0.081
Nigeria	0.867	0.901	3.351	27.645	27830.7	0.000	0.104
South Africa	1.143	1.014	1.795	7.398	1375.0	0.000	0.069
Tunisia	0.454	0.382	1.561	6.586	964.6	0.000	0.028
BCOM	0.8198	0.633	1.271	5.547	552.7	5.75E-07	0.048
MSCI-DW	0.520	0.452	1.581	6.356	907.1	8.00E-06	0.030
MSCI-EM	0.818	0.759	2.176	10.448	3174.6	0.000	0.060
East Africa	0.088	0.121	3.787	24.872	22858.7	0.000	0.012
North Africa	0.060	0.065	2.578	11.991	4582.6	5.59E-07	0.005
Southern Africa	1.134	1.008	1.791	7.376	1364.2	0.000	0.068
West Africa	0.759	0.771	2.695	17.898	10709.6	0.000	0.079
Panel B: Crisis period – 15th September, 2008 to 31st May, 2009							
Botswana	1.040	0.906	1.386	5.480	87.0	0.000	0.049
Egypt	0.729	0.708	1.182	4.171	43.8	0.000	0.033
Ghana	0.635	1.144	3.761	19.492	2067.3	0.000	0.071
Kenya	1.365	1.393	2.208	9.507	389.1	0.000	0.083
Morocco	1.522	1.382	1.672	6.547	149.5	0.000	0.074
Nigeria	1.627	1.538	1.566	6.896	157.2	0.000	0.089
South Africa	3.164	2.636	1.472	5.431	91.7	0.000	0.129
Tunisia	0.849	0.894	2.502	12.550	731.4	7.05E-05	0.064
BCOM	1.327	1.197	1.691	6.076	131.5	0.000	0.064
MSCI-DW	0.781	0.662	1.417	5.219	81.5	0.000	0.033
MSCI-EM	2.340	2.270	1.519	4.875	80.2	0.000	0.101
East Africa	0.236	0.256	1.987	7.292	215.3	0.000	0.014
North Africa	0.147	1.343	1.643	6.272	135.3	2.61E-05	0.007
Southern Africa	3.158	2.630	1.482	5.473	93.8	0.000	0.129
West Africa	1.519	1.280	1.680	7.831	217.7	0.000	0.079
Panel C: Post-crisis period – 1st June, 2009 to 29th December, 2014							
Botswana	0.551	0.530	2.594	15.737	11200.2	0.000	0.054
Egypt	1.089	1.393	2.322	10.464	4575.4	0.000	0.109
Ghana	0.651	0.787	2.562	11.849	6190.0	0.000	0.059
Kenya	0.548	0.538	2.607	14.589	9560.7	0.000	0.052
Morocco	0.973	0.981	2.354	11.637	5729.3	0.000	0.087
Nigeria	0.916	0.896	1.996	8.882	2992.6	0.000	0.073
South Africa	1.169	1.010	1.843	8.254	2438.4	0.000	0.076
Tunisia	0.511	0.492	2.597	13.856	8574.5	3.89E-06	0.038
BCOM	0.802	0.782	2.306	10.930	4983.8	3.00E-06	0.068
MSCI-DW	0.809	0.998	5.328	63.507	223487.3	0.000	0.173
MSCI-EM	0.755	0.693	1.984	9.924	3770.7	0.000	0.065
East Africa	0.092	0.093	2.167	10.011	4022.5	0.000	0.007
North Africa	0.078	0.088	2.933	16.023	12080.1	2.30E-07	0.008
Southern Africa	1.148	1.016	1.913	8.600	2723,3	0.000	0.076
West Africa	0.883	0.757	1.951	8.825	2910.4	0.000	0.063

Notes: *Std.: standard deviation; Skew: skewness; kurt: kurtosis; JB.: Jarque-Bera; Min.: Minimum; Max.: Maximum. Volatilities are based on absolute returns.*

As a prelude to examining shocks spillover, we analyze the level of correlation between the African markets on one hand, and each of the regional and global counterparts on another hand across sub-samples. Effectively, contagion draws the correlations between markets to unity, condenses possible diversification opportunities, and defeats the theoretical implication of the decoupling hypothesis. African markets are characterized by returns behaviour that is lowly correlated with that of developed markets (see Moss and Thuotte, 2013). Thus, the possibility of alleviating overall portfolio risk with the inclusion of securities from emerging markets in a portfolio of only developed markets assets is very high. Bekaert and Harvey (2014) stressed the need for correlation analysis on account that because investors will only invest a proportion of their portfolio investment in emerging markets, correlation serves as a significant driver of the ultimate risk borne. We show the volatility cross-market correlations in our sample in Table 4.2 for the pre, during, and post-crisis periods of the GFC. In the first panel, the upper (lower) triangle contains pre-crisis (crisis) period correlations, whilst the second panel contains the post-crisis period correlations. In line with the objective of this chapter (i.e. focus on regional vs. global shocks spillovers), we decline analyzing all individual country specific market-to-market and regional-to-global market cross-correlation pairs and limit the discussion to cross-market regional and global correlations.

We find the number of individual cross-market correlations (between each African market and each of the regional and global markets) greater than 0.05 to be 19, 28, and 27 for the pre, during, and post-crisis periods respectively. During the pre-crisis period, the highest regional correlations of 0.935, 0.956, and 0.999 were recorded for the West Africa/Nigeria, North Africa/Morocco, and Southern Africa/South Africa market pairs respectively. In the crisis period, the regional correlation pairs are 0.989 (West Africa/Nigeria); 0.999 (North Africa/Morocco); and 0.999 (Southern Africa/South Africa). In the post-crisis period also the correlation pairs are 0.991 (West Africa/Nigeria); 0.955 (North Africa/Morocco); and 0.997 (Southern Africa/South Africa). The relatively high correlations, exceeding 50% (in both frequency and intensity) in the crisis period indicate stronger linkages between the markets or more common shocks. Although regional correlations for the other African markets are relatively lower, they are still substantial and at levels generally higher than the global correlations. In fact, all correlations between individual African markets and global counterparts are below 10%. The only exceptions above 10% happen during the crisis period between the MSCI-EM and the Kenya stock market. The above findings indicate that not only did the number of global correlations increase during the 2007-2009 global financial crisis, but also the intensity heightened. The results lay credence to Forbes and Rigobon (2002)'s shift contagion theory of increases in cross-market correlations during crisis. It must however be emphasized that the cross-market correlations appear highly regionally driven than globally. We however wish to comment that although the correlations shown in Table 4.3 give some indication of co-movement and interdependence, they do not necessarily reflect the dynamic nexus between or among the markets since they are static measures.

Further to the correlation analysis, we estimate Equations (4.3.3) and (4.3.4) to examine the presence or otherwise of shocks spillover (i.e. decoupling or recoupling) from regional and global markets to their African counterparts. The intuition is that, if two markets exhibit common stochastic trends over time, then shocks from one market may be transmitted to the other. We assume that shocks spill-overs may be regionally or globally driven and time-varying. We in turn analyze individual regional and global shock spillovers (see sub-section 4.4.3), as well as joint shocks from regional and global markets (in sub-section 4.4.4).

4.4.3 Spillovers from regional and global markets

Table 4.3a shows results based on Equation (4.3.3) in which separate shocks from regional or global markets are estimated in Panels A-C corresponding to the pre, during, and post-GFC periods, respectively. Before analyzing the results let us clarify some specifications. The coefficient parameters $\theta_1, \theta_2, \theta_3$, and θ_4 (suppressed in Equation – 4.3.3), respectively relate to shocks from East Africa, North Africa, Southern Africa, and West Africa. Similarly, γ_1, γ_2, and γ_3 indicates shocks from BCOM, MSCI-DW, and MSCI-EM, respectively. Consistent with the correlation results, the parameter estimates indicate that the level of spillovers is higher regionally than globally.
The outcome is consistent with Sugimoto *et al.,* (2014) who report that regional spillovers for Zambia surpassed global spillovers several times. We cautiously infer that the regionally driven cross-border spillover effects may reflect the degree of regional integration (see Piesse and Hearn, 2005; for evidence of some degree of regional integration), real sector linkages, as well as the level of openness among countries.

Thus, arguably, the significant gains in ensuring economic integration, the removal of some barriers to intra-regional trade (Mougani, 2014), as well as various market liberalization programmes instituted in Africa may have fueled inter-regional financial integration leading to increases in spillover effects. We however, do not by any means imply complete regional financial markets integration in Africa. Clearly, the results generally indicate substantial levels of decoupling/segmentation of individual markets from regional counterparts (since most of the coefficients are insignificant) and that effort to enhance stronger regional markets coordination ought to be pursued.

This can be done through harmonization of exchange rate mechanisms and intensification of trade and other cooperation among national governments to wipe-away obstacles to free flow of investment capital across regions and countries. Whilst spillovers from regional markets in tranquil periods is more prevalent than the crisis period, the evidence of spillover effects from global markets is mixed – more in the post-crisis, less in pre-crisis, and moderate during the crisis period.

The Southern Africa regional market is identified to be the most influential market exerting spillover effects to four markets in the pre-crisis period - 5 during the crisis and 6 post-crisis. The spillover effects of the North African regional market in the crisis period are also almost at similar levels as that from the Southern African markets. For this reason we cannot conclude at this moment that the Southern African markets have dominance over other regional counterparts in terms of spillover effects (see also Sugimoto *et al.,* 2014). South Africa and Nigeria are the most responsive markets to regional contagion during the crisis. Unsurprisingly, these markets are among the largest on the

Table 4.2: Contemporaneous correlations of volatilities

Upper triangle: pre-crisis **Lower triangle:** crisis period	**BCOM**	**Botswana**	**East Africa**	**Egypt**	**Ghana**	**Kenya**	**Morocco**	**MSCI-DW**	**MSCI-EM**	**Nigeria**	**North Africa**	**South Africa**	**Southern Africa**	**Tunisia**	**West Africa**
BCOM		**0.059**	-0.008	**0.074**	0.048	-0.023	0.021	-0.027	0.030	0.026	0.030	0.019	0.019	0.032	0.039
Botswana	**0.056**		-0.008	-0.005	0.457	0.153	0.085	-0.040	0.010	0.034	**0.111**	0.030	0.041	0.083	**0.234**
East Africa	0.014	0.024		0.008	-0.021	0.033	-0.002	0.042	0.057	**0.070**	0.032	**0.094**	0.094	**0.067**	0.063
Egypt	-0.003	0.033	**-0.061**		0.028	-0.017	0.002	-0.001	-0.028	0.025	0.001	**-0.058**	**-0.058**	0.008	0.034
Ghana	**-0.067**	-0.121	**-0.101**	-0.042		0.068	-0.012	-0.018	-0.004	0.023	-0.015	-0.016	-0.010	0.061	**0.296**
Kenya	-0.041	0.251	0.019	-0.099	-0.016		-0.012	0.007	0.031	-0.046	0.021	0.050	**0.051**	0.026	-0.029
Morocco	0.034	0.130	**0.153**	-0.038	-0.066	0.121		-0.045	-0.035	-0.012	**0.956**	0.140	**0.141**	0.076	-0.008
MSCI-DW	0.018	0.042	0.037	**-0.056**	-0.050	-0.047	**0.144**		0.038	0.003	-0.039	0.037	0.037	0.024	-0.003
MSCI-EM	-0.016	**0.194**	0.126	**-0.089**	-0.074	**0.289**	0.047	-0.118		-0.044	-0.009	**0.061**	0.061	0.009	-0.033
Nigeria	0.023	0.025	**-0.111**	0.049	0.004	0.223	-0.011	-0.016	0.026		-0.014	-0.037	-0.037	0.024	**0.935**
North Africa	0.033	**0.135**	0.160	-0.045	-0.070	**0.134**	**0.999**	0.140	0.064	-0.009		**0.189**	0.190	**0.077**	-0.003
South Africa	0.029	0.420	**0.204**	-0.102	-0.059	0.087	0.182	**0.097**	0.018	-0.036	**0.197**		**0.999**	0.159	-0.023
Southern Africa	0.029	**0.423**	0.204	**-0.103**	-0.059	**0.089**	**0.183**	0.098	0.021	-0.036	0.198	**0.999**		**0.160**	-0.020
Tunisia	**0.086**	0.322	**0.178**	-0.045	0.034	0.095	0.295	0.003	0.046	-0.122	**0.311**	0.438	0.439		0.048
West Africa	0.020	0.048	-0.114	0.035	0.052	**0.224**	0.029	-0.022	0.036	**0.989**	0.032	-0.005	-0.004	**-0.083**	
Post-crisis period															
BCOM		**0.093**	0.131	0.006	-0.035	**0.092**	**-0.064**	0.116	0.108	0.030	-0.080	**0.091**	0.100	**0.079**	0.029
Botswana			**0.068**	0.014	0.015	0.080	0.026	**0.083**	0.031	0.044	-0.010	0.397	**0.412**	0.093	0.049
East Africa				**0.072**	-0.015	**0.077**	-0.017	0.103	0.104	**0.134**	-0.009	**0.132**	0.135	**0.064**	0.130
Egypt					0.041	0.004	-0.022	0.031	-0.005	0.009	-0.026	-0.003	0.002	0.012	0.012
Ghana						0.002	-0.054	-0.041	-0.047	-0.009	-0.028	-0.024	-0.025	-0.040	0.036
Kenya							-0.015	0.015	**0.069**	0.103	-0.042	0.136	**0.141**	0.026	**0.107**
Morocco								**-0.081**	**-0.063**	0.031	**0.955**	0.034	0.030	0.019	0.032
MSCI-DW									0.085	0.048	-0.083	**0.077**	0.084	-0.022	0.039
MSCI-EM										**0.053**	-0.076	**0.080**	0.083	0.009	0.050
Nigeria											0.047	0.087	**0.088**	0.025	**0.991**
North Africa												-0.021	-0.028	0.001	0.046
South Africa													**0.997**	0.109	**0.099**
Southern Africa														**0.113**	0.010
Tunisia															0.043
West Africa															

Notes: *The table shows volatility cross-correlation matrix among markets in our sample from 3rd January, 2003 to 29th December, 2014 segmented into pre (upper triangle in first panel), crisis (lower triangle in first panel), and post (second panel) crisis periods. Volatilities are based on absolute returns.*

continent and appear to have the most de-facto levels of regional integration. Additionally, the markets in South Africa and Nigeria have large composition of listings of multinational corporations from other parts of the continent. Hence, crashes in domestic economies in Africa affect these markets through the listed companies' reduced performances.

We find the MSCI-EM index as the only global market to have significantly exerted spillover effects on individual African markets (namely, Botswana, Morocco, Kenya, and South Africa) during the crisis. The significant responsiveness of Kenya, Botswana and South Africa to shock from MSCI-EM other than the non-crisis periods may be dependent on their level of integration, liquidity levels or shocks from the real sector.[53] For South Africa, the spill-over effects was felt through a deteriorating overall economy which heightened pressure on the country's balance of payment with consequential effects on domestic exchange rates, overall gross domestic product (GDP) and financial sectors, without corresponding increases in portfolio investments flows (see Simatele, 2014).

It is also important to note that the South African market remains Africa's most integrated market with other emerging markets (see Alagidede, 2010; Agyei-Amponsah, 2011; Chinzara and Kambadza, 2014). Botswana and Kenya remain Africa's most opened markets with capital market developments strongly driven by foreign companies despite their small market sizes. Lower diamond sales to the financially depressed European markets during the 2007-2009 crisis made Botswana's domestic economy highly vulnerable to shifts in global economies that consume the country's diamond (see also Ahmed and Mmolainyane, 2014). Though other individual domestic markets show resilience to shocks from the global markets during the crisis, we are careful not to infer that these markets would be completely immune to global shocks contagion during crisis or suggest that policy actions undertaken by national governments was adequate to offset any potential effects of international market shifts.

[53] Spill-overs may be higher in liquid (highly integrated) markets than in thinner (purely segmented) markets.

Table 4.3a: Estimated coefficients of regional and global shocks

	Eq. [4.3.3] - $\varepsilon_t^d = \theta_i(\varepsilon^{R_i})_t + \gamma_i(\varepsilon^{G_i})_t + \eta_t$						
	Co-efficient of regional shocks				**Co-efficient of global shocks**		
African markets	θ_1	θ_2	θ_3	θ_4	γ_1	γ_2	γ_3
Panel A: Pre-crisis period – 3rd January, 2003 to 14th September, 2008							
Botswana	-0.303	2.121*	0.036	0.402*	0.093	-0.101	0.033
Egypt	0. 154	0.209	-0.086***	0.052	0.168**	0.013	-0.050
Ghana	-0.358	-0.264	0.002	0.430*	0.063	-0.039	0.010
Morocco	-0.179*	11.486*	-0.029*	-0.005	-0.009	-0.007	-0.023**
Nigeria	0.102	-0.131	-0.015	1.091*	-0.013	0.010	-0.015
South Africa	0.003	-0.020*	1.007*	-0.003*	-0.000	0.001	-0.000
Tunisia	0.153	0.278	0.056*	0.023	0.016	0.016	-0.001
Kenya	0.217	0.180	0.040	-0.033	-0.034	0.006	0.032
Panel B: Crisis period – 15th September, 2008 to 30st May, 2009							
Botswana	-0.328	0.326	0.147*	0.021	0.035	0.028	0.078*
Egypt	-0.065	-0.058	-0.024	0.019	-0.001	-0.058	-0.028
Ghana	-0.319	-0.355	-0.012	0.043	-0.062	-0.077	-0.035
Morocco	-0.017	10.315*	-0.007*	-0.003	0.002	0.006	-0.010*
Nigeria	0.082	-0.446*	-0.016**	1.192*	0.007	0.027	-0.005
South Africa	0.001	-0.018**	1.002*	-0.001	1.96E-06	-0.001	-0.003*
Tunisia	0.180	1.568*	0.131*	-0.061	0.052	-0.096	0.005
Kenya	-0.114	1.083	0.038	0.228*	-0.053	-0.064	0.167*
Panel C: Post-crisis period – 1st June, 2009 to 29th December, 2014							
Botswana	0.020	0.046	0.211*	0.004	0.033**	0.023***	-0.009
Egypt	1.081*	-0.401	-0.013	0.008	0.010	0.034	-0.032
Ghana	-0.055	-0.348	-0.015	0.046***	-0.027	-0.029	-0.050
Morocco	-0.166**	10.690*	0.058*	-0.021**	0.011	-0.006	0.010
Nigeria	0.052	0.026	-0.011*	1.172*	0.001	0.008*	0.004
South Africa	-0.012	0.078*	1.022*	-0.001	-0.010*	-0.005**	-0.002
Tunisia	0.227	0.020	0.050*	0.018	0.043**	-0.021	-0.006
Kenya	0.033	-0.216	0.062*	0.063*	0.046**	-0.009	0.033

Notes: θ_1, θ_2, θ_3, *and* θ_4 *respectively relate to shocks from East Africa, North Africa, Southern Africa, and West Africa. Similarly,* γ_1, γ_2, *and* γ_3 *indicates shocks from BCOM, MSCI-DW, and MSCI-EM respectively. "*, **, ***" denote statistical significance at the 1%, 5%, and 10% levels respectively.*

Another interesting finding from Table 4.3a is that none of the African markets is identified to be responsive to shocks from BCOM, MSCI-DW, and the East African regional markets index during the crisis period. The evidence of Africa's decoupling from global shock spillovers (particularly, from BCOM and MSCI-DW) may reflect low levels of foreign investors' participation in the domestic markets. For instance, despite the increases in private capital flows into Sub-Saharan Africa (SSA) in the early days of the 21st century, the advent of the 2007-2009 global financial crisis (GFC) registered some declines due to increased investor risk-aversion, tighter global credit conditions, and developments in the bond markets (Simatele, 2014).

Although there appears to be some recovery from Africa's bond and equity markets post-crisis, the gains still remain a minuscule proportion of the overall global equity and bond markets returns (see also AfDB, 2013; Simatele, 2014). The reasons for the above may be partly due to problems of home bias and other factors that remain as critical hindrances to foreign investors such as constraints relating to poor governance structures, small market sizes, lack of liquidity, political unrest, etc.[54] Additionally, problems of high inflation, lack of proper securities regulation and supervision, macro-economic unsteadiness, returns volatility, and exchange rate exposures are apparent – see also Moss and Thuotte (2013) and Alagidede, (2008).

4.4.4 Joint regional and global spillovers

For now we have examined spillovers from global or regional markets individually to isolated African stock markets. Meanwhile, particularly for emerging/developing markets, transmission of shocks from global markets may not be direct but through other channels. However, at this point, we do not analyze real sector linkages that may serve as conduits for the propagation of shocks from global markets to individual African counterparts since our model is not advantaged in that regard. Instead, we assume that each aggregated market index from a particular region in Africa apart from transmitting its own shock to other individual domestic markets may also receive and propagate shocks from global markets. If a regional market is identified not to have been able to transmit its own shocks to a particular market (as in Table 4.3a) but is able to do so after interacting with a global market, such regional market will be deemed a '*transmitter*' of global shocks. Otherwise, if the regional market is able to transmit its own shock to markets (in Table 4.3a) but fail to transmit shocks to markets aside the ones it was able to influence in Table 4.3b, such a regional market will be classified as just a shock '*receiver/absorber*'.

In Table 4.3b, shocks arising from the interaction of each regional and individual global market are presented in a manner similar to Table 4.3a to reflect the pre, during, and post-GFC periods. The parameters, $\phi_1, \phi_2, \ and \ \phi_3$ denote coefficients of shocks generated from regressing each regional-global market interactive shocks on individual African stock markets shocks. Thus, $\phi_1, \phi_2, \ and \ \phi_3$,

[54] For instance the Jasmine revolution in Tunisia at the end of 2010, the mass protest in Egypt in 2010, the post electoral violence in Kenya in 2008, and the seemingly perpetual 'Boko-haram' militancy in Nigeria.

respectively correspond to regional/BCOM, regional/MSCI-DW, and regional/MSCI-EM interactive shocks. The regional markets are shown in the columns above the parameters.

We find across the different sub-samples that regional markets that failed to transmit their own shocks to individual markets are able to exert spillover effects after interacting with the global markets. Additionally, global markets that failed to propagate shocks from their own market shifts to other individual African markets are able to do so through the regional markets. For instance, although in Table 4.3a, aggregate shocks from the East African region could not influence any individual domestic market in the continent during the crisis, the story is different in Table 4.3b. For the global markets, both BCOM and MSCI-DW markets which were unable to transmit shocks to the domestic African markets in Table 4.4a during the crisis period are able to do so through three regional markets - North Africa, Southern Africa, and West Africa.

A careful examination of the results in Table 4.3b shows that each regional market acts as a transmitter/carrier of international shocks to one domestic market or another. This implies that policy coordination in Africa for financial markets integration should, among other things include efforts capable of alleviating the spread of common shocks in the continent. This calls for Africa's unity in fighting the continent's susceptibility to global shocks contagion since a global 'cold' caught by one member country can easily spread to others.

Only the Southern African and West African regional markets could transmit shocks from the developed world market (MSCI-DW) to domestic markets in Africa during the crisis period. This may be due to the fact that South Africa and Nigeria, which are the most integrated globally in their respective regions, and arguably the two largest economies on the African continent, dominate the composition of their regional aggregates and have higher numbers of listed firms on the local bourses which are also in the international register. Therefore sell-offs in the international markets could easily trigger shocks to them and affect other local markets they are closely associated with.

Table 4.3b: Estimated coefficients of joint regional and global shocks

Eq. [4.3.4] - $\varepsilon_t^d = \phi_i \left(\varepsilon^{R*}\right)_t + \eta_t$

African markets	East Africa			North Africa			Southern Africa			West Africa		
	ϕ_1	ϕ_2	ϕ_3	ϕ_1	ϕ_2	ϕ_3	ϕ_1	ϕ_2	ϕ_3	ϕ_1	ϕ_2	ϕ_3
Panel A: Pre-crisis period – 3rd January, 2003 to 14th September, 2008												
Botswana	-3.76	7.57	-3.88	-33.73***	-16.62	52.55**	-1.94***	1.99**	0.00	-2.05	1.44	1.01
Egypt	0.05	-3.87	3.92	-43.16**	5.80	37.34	-1.90	0.88	0.94	-3.47**	5.15**	-1.62
Ghana	-1.37	1.82	-0.64	-23.33	-5.94	28.97	-1.17	0.94	0.22	-1.29	1.46	0.26
Morocco	-9.16	5.90	3.28	6.62***	-0.39	5.17	-1.26**	0.87	0.50	-0.50	1.46	-0.97
Nigeria	-3.92	-1.29	5.75	-6.04	4.46	1.38	-0.73	0.01	0.68	0.30	1.25**	-0.45
South Africa	15.34**	-6.56	-8.03***	15.54	12.80	5.67	0.75*	0.19*	0.07*	-0.69	-1.54	2.21***
Tunisia	2.58	-1.95	-0.43	-5.98	3.92	2.51	0.02	-0.02	0.06	-0.40	0.31	0.11
Kenya	3.523	0.062	-3.345	6.196	-0.097	-5.794	0.723	-0.215	-0.463	0.683	-1.780	1.065
Panel B: Crisis period – 15th September, 2008 to 31st May, 2009												
Botswana	8.21	-2.95	-5.26**	14.39***	-0.56	12.99***	0.70	0.08	-0.64	-0.14	3.62***	-3.45**
Egypt	-5.89	3.89	1.86	0.02	0.24	-0.43	-0.45	0.10	0.32	0.17	-1.65	1.50
Ghana	-5.13	2.73	1.99	-5.79	1.48	3.77	0.05	0.11	-0.19	1.73	-3.42	1.74
Morocco	18.74	-16.57	1.40	5.58*	0.29	4.42*	0.40	-0.60	0.29	-3.68	6.07***	-2.36
Nigeria	-1.60	2.63	-1.72	0.32	1.62	-2.02	-0.14	0.11	0.00	0.22	0.54	0.42
South Africa	21.17	19.52	0.42	10.32	-8.64	1.99	0.28*	0.04*	0.68*	-5.34	7.65	-2.32
Tunisia	-1.97	2.91	-0.32	-2.23	2.78	1.57	-0.42	0.19	0.38	-1.22	1.67	-0.51
Kenya	11.218	1.246	-12.554*	35.891*	3.821	-38.394*	2.821**	0.387	-3.157**	5.643***	2.161	-7.568*
Panel C: Post-crisis period – 1st June, 2009 to 29th December, 2014												
Botswana	-1.60	-0.54	2.48**	2.13	1.33	-3.49**	-0.09	-0.02	0.33*	-0.03	-0.28	0.35
Egypt	0.99	-2.84	2.93	-1.03	4.34	-3.71	0.05	-0.35	0.30	0.56	-1.09	0.55
Ghana	-0.08	-0.30	0.29	0.72	-0.34	-0.66	-0.02	-0.03	0.03	-0.60	0.17	0.47
Morocco	0.42	0.70	-1.21	4.32*	2.02**	4.36*	0.05	0.11	-0.12	-1.10	0.70	0.44
Nigeria	1.30	0.25	-0.28	-1.77	1.06	1.24	0.13	0.00	-0.05	0.85*	0.15	0.17**
South Africa	-1.37	1.61	1.15	1.40	-0.42	-1.14	0.29*	0.39*	0.35*	0.66	0.01	-0.54
Tunisia	-2.75*	2.44**	0.62	4.52*	3.32**	-1.19	-0.32*	0.29**	0.08	-1.10**	0.94**	0.19
Kenya	-2.023***	2.900**	-0.477	2.797	-3.548**	0.518	-0.218***	0.334**	-0.044	-0.457	0.875	-0.343

Notes: ϕ_1, ϕ_2 *, and* ϕ_3 *denotes coefficients of shocks from regional-BCOM, regional-MSCI-DW, and regional-MSCI-EM interactions. The regional markets are shown in the columns above coefficients. "*, **, ***" denote statistical significance at the 1%, 5%, and 10% levels respectively.*

4.5 Conclusion

We examined whether 8 African stock markets (namely, Ghana, Nigeria, South Africa, Botswana, Morocco, Tunisia, Egypt, and Kenya) decoupled from or converged with both regional and global markets from 2003 to 2014, and analyzed the implications of that for shocks spillovers. We first examined convergence within the unit roots framework and latter modeled shock spillovers in a step-wise OLS framework. Our modeling of shocks propagation takes into account the effects of the 2007-2009 global financial crisis using a CAPM based analytic framework. The global indices captured enable us to focus on shocks coming from the aggregate market for developed economies, emerging economies, and the commodity markets. An estimable data is constructed for all the four regional markets grouped into East Africa, North Africa, West Africa, and Southern Africa. We disaggregated the data into pre-, during-, and post-crisis periods to enable us capture the spillover of shocks in each sub-sample. Apart from examining whether individually shocks from a regional or global index spread to domestic markets in Africa, our model also allows us to determine regional markets that act as just shock 'receivers/absorbers' or 'transmitters'.

Our results from all sampled series exhibit higher mean returns and standard deviations (our crude measure of risk) during the crisis than tranquil periods, with the highest values recorded for the global markets. The probability distributions are also skewed to the right and have leptokurtic behaviour with fat tails than a corresponding normal distribution. We found evidence of higher increases in correlation (in both frequency and intensity) in the crisis period relative to non-crisis periods, supporting the theoretical proposition on shift contagion (see Forbes and Rigobon, 2002). The cross-market correlations appear highly regionally driven than globally.

Surprisingly, we found no evidence of convergence either regionally or globally for the African stock markets during the entire sample period. Despite this, spill-over effects are established in a time-varying setting. Consistent with the correlation results, we found that the level of regional spillovers is higher than for global across sub-samples. During the crisis, while shocks from regional markets such as North Africa, Southern Africa, and West Africa spilled to individual African markets, we found the emerging markets index (MSCI-EM) to be the only global market that is able to spread shocks to individual African markets. This implies higher levels of African markets decoupling from global shocks during the crisis than from regional shocks. The Southern African regional market is identified as the most influential in exerting spillover effects during the crisis.

We cautiously infer that the sensitivity of individual domestic markets to shocks from regional blocks may be dependent on the degree of openness and integration, as well as level of macroeconomic coordination between countries. Thus, the significant gains in ensuring economic integration, the removal of some barriers to intra-regional trade (Mougani, 2014), as well as various market liberalization programmes instituted in Africa may have fueled inter-regional financial integration leading to the increases in spillover effects. We however, do not by any means imply complete regional financial markets integration in Africa. Clearly, the results also generally indicated substantial levels of decoupling/segmentation of individual markets from regional counterparts (since most of the coefficients are insignificant) and that effort to enhance stronger regional markets coordination ought to be pursued. This can be done through harmonization of exchange rate mechanisms and intensification of trade and other cooperation among national governments to reduce barriers to free flow of investment capital cross regions and countries. Whilst spillovers from regional markets in tranquil periods is more prevalent than the crisis period, the evidence of spillover effects from global markets is mixed – more in the post-crisis, less in pre-crisis, and moderate during the crisis period.

The results further indicated that across the different sub-samples regional markets that failed to transmit their own shocks to individual markets are able to exert spillover effects after interacting with the global markets. Additionally, the spillover of shocks from some global markets (particularly, BCOM and MSCI-EM) to individual markets in Africa could only occur through the regional markets. This leads to our conclusion that apart from propagating their own shocks, each regional market also acts as a transmitter/carrier of international/global shocks.

References

Ahmed, D.A., Mmolainyane, K.K., (2014). Financial integration, capital market development and economic performance: Empirical evidence from Botswana. *Economic Modeling*, 42:1-14.

Agyei-Amponsah, S., (2011). Stock market integration in Africa. *Managerial Finance*, 37(3): 242-256.

African Development Bank (2013). Situational analysis of the reliability of economic statistics in Africa: special focus on GDP measurement. *African Development Bank*, Tunis.

Alagidede, P., (2008). African stock market integration: implications for portfolio diversification and international risk sharing. *Proceedings of the African Economic Conference* 2008, pp. 26 – 54.

Alagidede, P., (2010). Equity market integration in Africa. *African Review of Economics and Finance,* 1(2): 88-119.

Asongu, S.A., (2012). African financial development dynamics: Big time convergence. *AGDI Working Paper* WP/12/003, pp. 2-47.

Asongu, S.A., (2013). African stock market performance dynamics: A multidimensional convergence assessment. *Journal of African Business*, 14(3):186-201.

Barro, R.J., Sala-i-Martin, X., (1992). Convergence. *Journal of Political Economy*, 100(2):223-251.

Baumol, W.J., (1986). Productivity growth, convergence and welfare: What the long run data show. *American Economic Review*, 76:1072-1085.

Bekaert, G., Harvey, C. R., (1995). Time-varying world market integration. *Journal of Finance*, 50(2):403-444.

Bekaert, G., Harvey, C. R., (2014). Emerging equity markets in a globalizing world. *Available at SSRN: http://ssrn.com/abstract=2344817 or http://dx.doi.org/10.2139/ssrn.2344817*

Benard, A.B., Durlauf, S.N., (1995). Interpreting tests of the convergence hypothesis. *Journal of Econometrics*, 71:161-173.

Berger, D., Pukthuanthong, K., Yang, J.J., (2011). International diversification with frontier markets. *Journal of Financial Economics,* 101: 227-242.

Boako, G., Omane-Adjapong, M., Frimpong, J.M. (2016). Stock returns and exchange rate nexus in Ghana: A Bayesian quantile regression approach. *South African Journal of Economics*, 84:149-179. DOI: 10.1111/saje.12096.

Brada, J.C., Kutan, A.M., Zhou, S., (2005). Real and monetary convergence between European Union's core and recent member countries: A rolling cointegration approach. *Journal of Banking and Finance,* 29:249-270.

Brooks, C., Persand, G., (2001) Seasonality in Southeast Asian stock markets: Some new evidence on Day-of-the-Week effect. *Applied Economics Letters* 8:155—8

Carlino, G.A., Mills, L., (1996). Testing neoclassical convergence in regional incomes and earnings. *Regional Science and Urban Economics*, 26:565-590.

Chatfield, C., (2003). The analysis of time series: An introduction (6th Edition ed.). London: Chapman and Hall.

Chinzara, Z., Kambadza, T.H.D., (2014). Evidence of segmentation among African equity markets. *The African Finance Journal*, 16:19-38.

Cochrane, J.H., (1988). How big is the random walk component in GNP? *Journal of Political Economy,* 96:893-920.

Coudert, V., Herve, K., Mabille, P., (2013). Internationalization vs. regionalization in the emerging stock markets. *CEPII, WP* No. 2013-08, pp. 1-28.

Dooley, M., Hutchison, M., (2009). Transmission of the U.S. sub-prime crisis to emerging markets: Evidence on the decoupling-recoupling hypothesis. *Journal of International Money and Finance,* 28:1331 – 1349.

Dungey, M., Gajurel, D., (2015). Contagion and banking crisis – international evidence for 2007-2009. *Journal of Banking and Finance*, 60:271-283.

Engle, R., (2004). Risk and volatility: Econometric models and financial practice. *American Economic Review,* 94(3):405-420.

Fitz-Gerald, K., (2010). Fiscal hangover: How to profit from the new global economy, *Wiley, Hoboken, NJ*: in- willet *et al.,* (2011). Global contagion and the decoupling debate. *Frontiers of Economics and Globalization*, 9:15-234.

Forbes, K.J., Rigobon, R., (2002). No contagion, only interdependence: Measuring stock market co-movements. *The Journal of Finance*, LVII: 2223 – 2261.

Fung, M.K., (2009). Financial development and economic growth: Convergence or divergence? *Journal of international Money and Finance*, 28:56-67.

Furstenberg Von, G.M., Jean, B.N., (1989). International stock price movements: Links and messages. *Brookings Papers on Economic Activity*, 1:125-179.

Gulko, L., (2002). Decoupling: If the U.S treasury repays its debts, what then? *The Journal of Portfolio Management,* 3:59-66.

IFC., (1999). The IFC Indexes: Methodology, definition, and practices. World Bank Emerging Markets Data Base. *Journal of Finance*, 55:529-564.

Kawai, M., Motonishi, T., (2005). Macroeconomic interdependence in East Asia. *Asian Economic Cooperation and Integration*: Progress, Prospects and Challenges. Manila: Asian Development Bank.

Kim, S.J., Moshirian, F., Wu, E., (2005). Dynamic stock market integration driven by the European Monetary Union: An empirical analysis. *Journal of Banking and Finance*, 29:2475-2502.

King, A., Ramlogan-Dobson, C., (2015). Is Africa actually developing? *World Development*, 66:598-613.

Lean, H.H., Nguyen, D.C., (2014). Policy uncertainty and performance characteristics of sustainable investments across regions around the global financial crisis. *Applied Financial Economics*, 24(21):1367-1373.

Li, Q., Papell, D.H (1999). Convergence of international output: Time series evidence for 16 OECD countries. *International Review of Economics and Finance*, 8(3):267-280.

Mougani, G., (2014). Challenges towards regional financial integration and monetary coordination in the West African Monetary Zone and the East African Community. *Regional Integration Policy Paper, African Development Bank*, pp. 1-56.

Moss, T.J., Thuotte, R., (2013). Nowhere to hide? Stock market correlation, regional diversification, and the case for investing in Africa. *Center for Global Development Working Paper* No. 316:1-20.

Narayan, P.K., Mishra, S., Nayaran, S., (2011). Do market capitalization and stocks traded Converge? A new global evidence. *Journal of Banking and Finance*, 3(10): 2771-2781.

Ntim, C.G., (2012). Why African stock markets should formally harmonize and integrate their operations. *African Review of Economics and Finance*, 4 (1): 53-72.

Odongo, K., Ojah, K., (2011). Foreign exchange risk pricing and equity market segmentation in Africa. *Journal of Banking and Finance*, 35: 2295-2310.

Pesaran, B., Pesaran, M.H., (2009). Time series econometrics using Microfit 5.0. *Oxford University Press,* pp. 237-248.

Piesse, J., Hearn, B., (2005). Regional integration of equity markets in Sub-Saharan Africa. *South African Journal of Economics*, 73(1): 36-52.

Priestley, M.B., (1981). Spectral analysis and time series. London Academic Press.

Senbet L.W., (2009). Financial sector policy reforms in the post financial crisis Era: Africa focus. *African Development Bank Working Paper, No. 100*, July 2009.

Senbet, L., Otchere, S., (2008). African stock markets. *African Finance for the 21st Century, Tunisia.*

Senbet, L.W., Gande, A., (2009). Financial crisis and stock markets: Issues, impact, and policies. *Annual Conference of the Dubai Economic Council, Dubai.*

Simatele, M., (2014). Reflections on the impact of the financial crisis on sub-Saharan Africa. *Africa Growth Agenda*, 18-24.

Solow, R.M., (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, LXX:65-94.

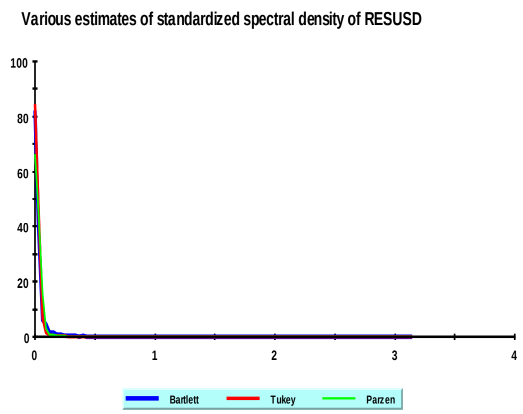
Sugimoto, K., Matsuki, T., Yoshida, Y., (2014). The global financial crisis: An analysis of the spillover effects on African stock markets. *Emerging Markets Review*, 21: 201-233.

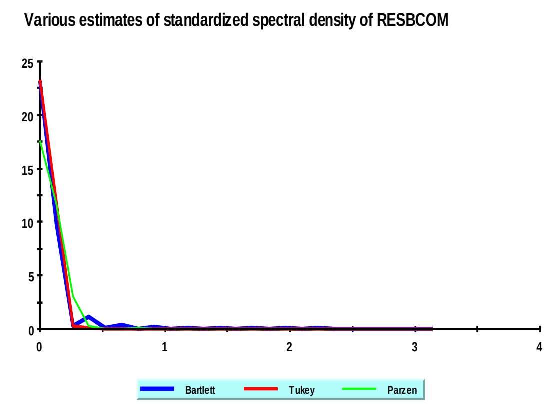
Willett, D.T., Liang, P., Zhang, N., (2011). Global contagion and the decoupling debate. *Frontiers of Economics and Globalization*, 9: 215-234.

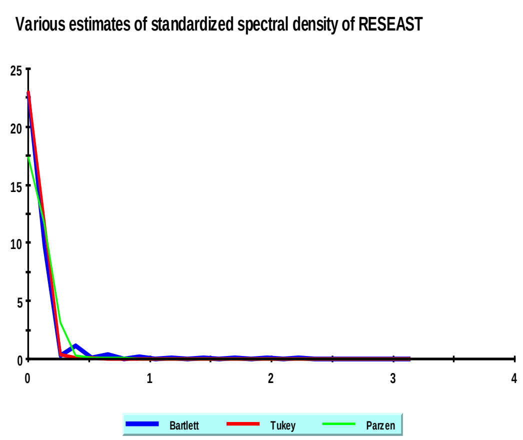
Zivot, E., Andrews, D.W.K., (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics*, 10:251-270.

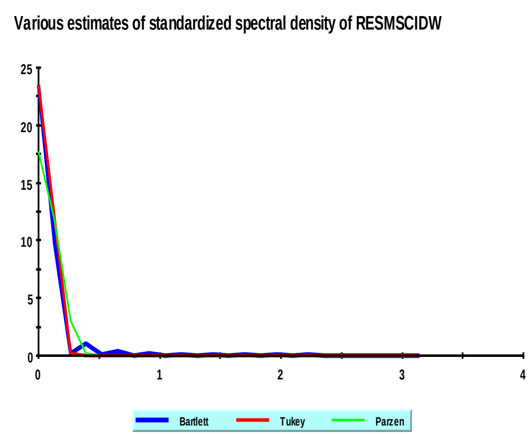
Appendix 4A: Results of spectral analysis using the BPT unit root tests.

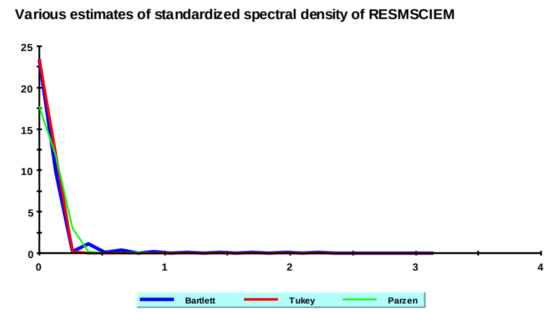
I: Morocco with all other markets – global, regional, and foreign exchange

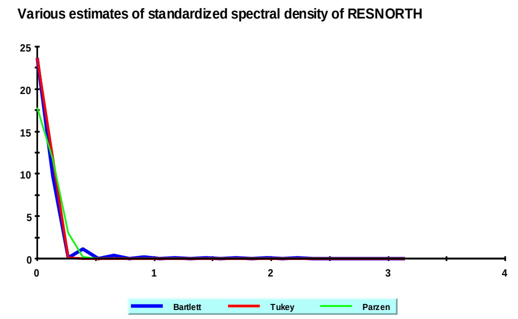


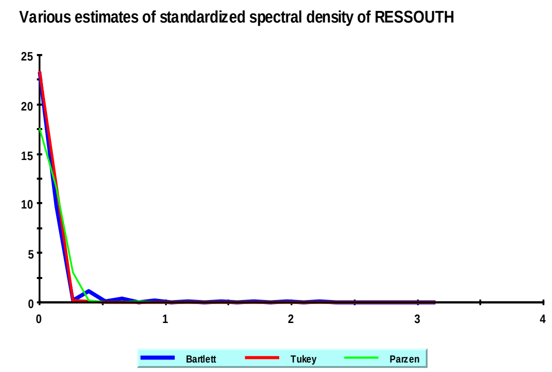


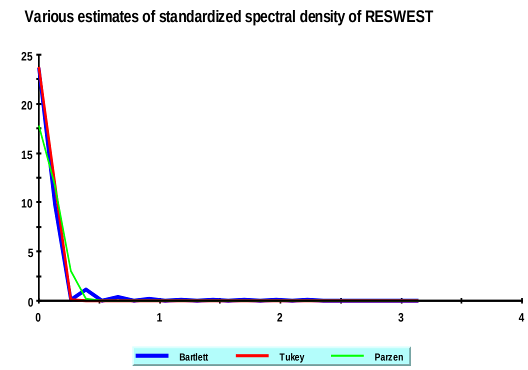




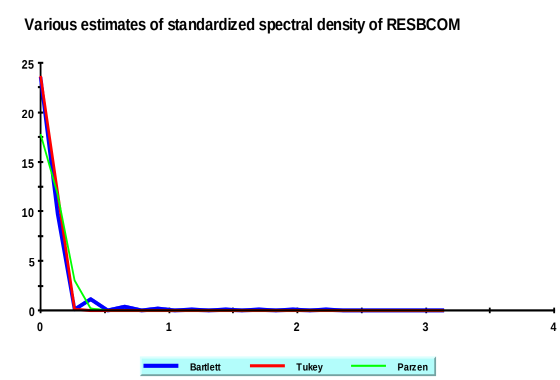


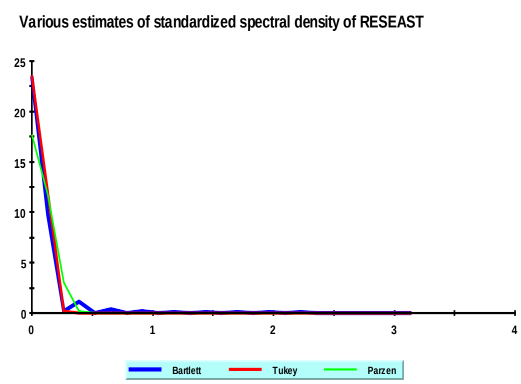




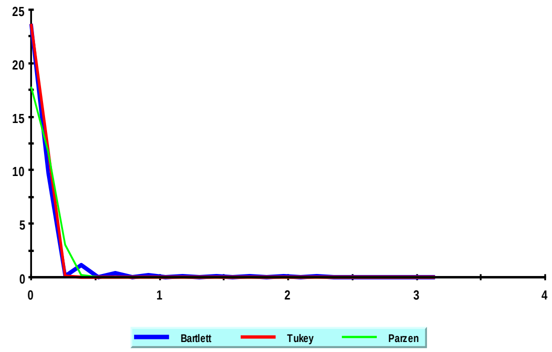


II: Egypt with all other markets – global, regional, and foreign exchange

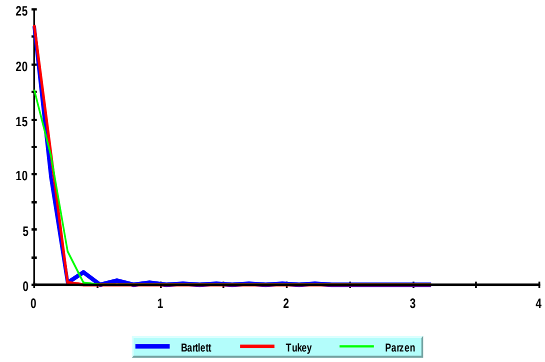




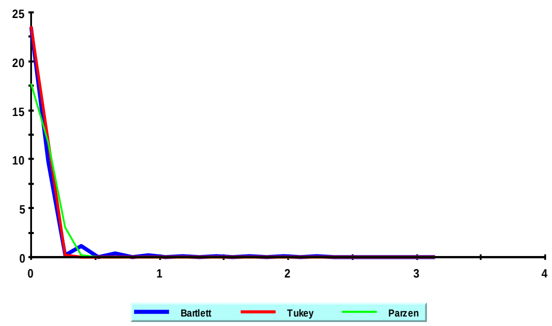
Various estimates of standardized spectral density of RESMSCIDW



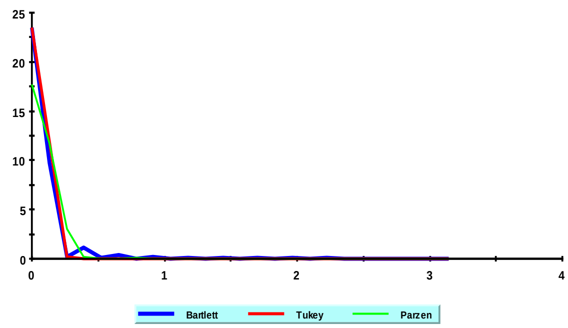
Various estimates of standardized spectral density of RESMSCIEM



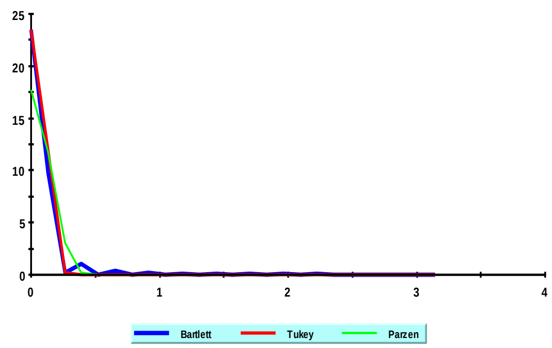
Various estimates of standardized spectral density of RESNORTH



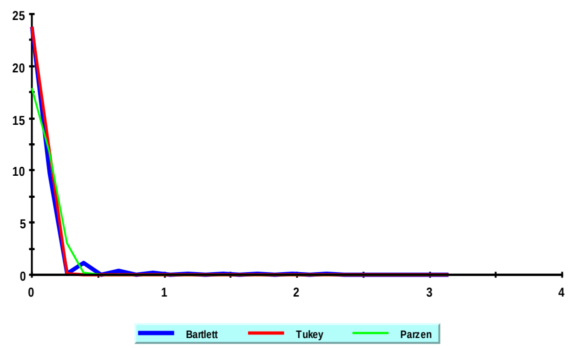
Various estimates of standardized spectral density of RESSOUTH



Various estimates of standardized spectral density of RESWEST

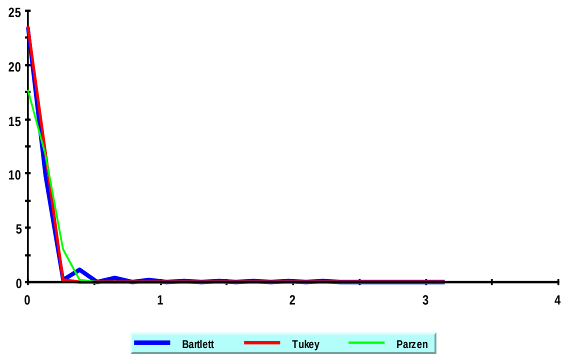


Various estimates of standardized spectral density of RESUSD

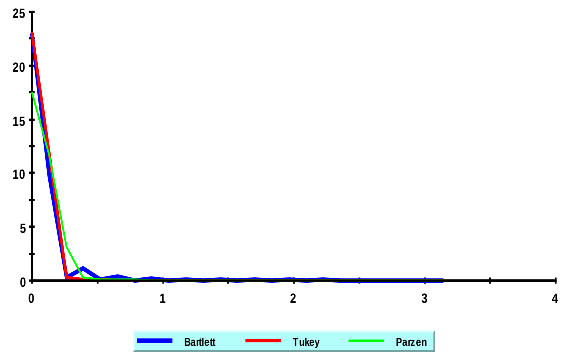


III: Tunisia with all other markets – global, regional, and foreign exchange

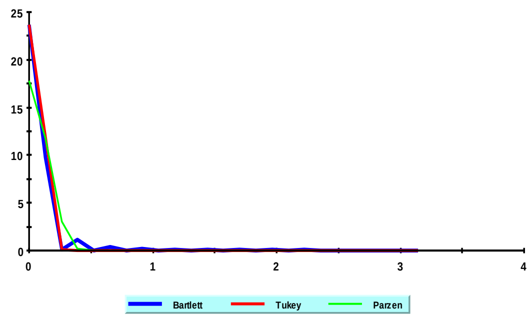
Various estimates of standardized spectral density of RESBCOM



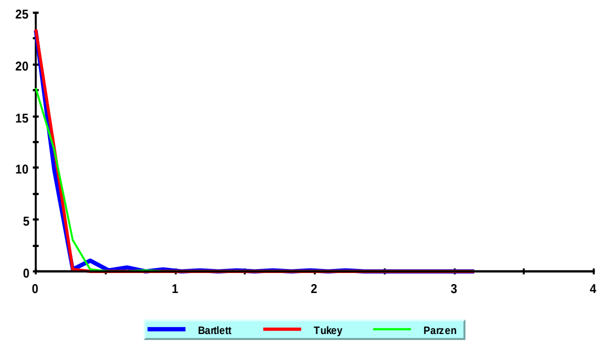
Various estimates of standardized spectral density of RESEAST



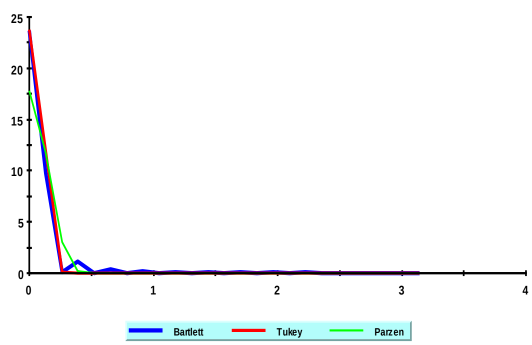
Various estimates of standardized spectral density of RESMSCIDW



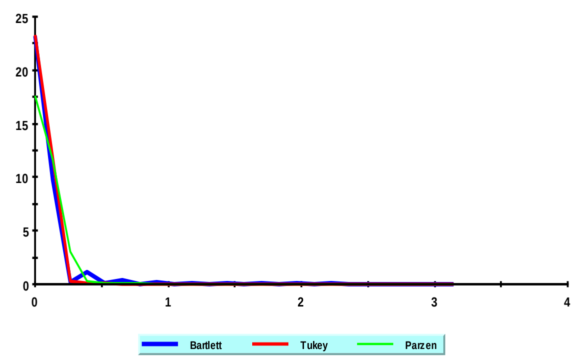
Various estimates of standardized spectral density of RESMSCIEM



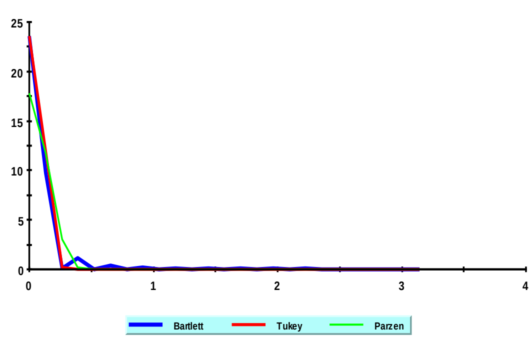
Various estimates of standardized spectral density of RESNORTH



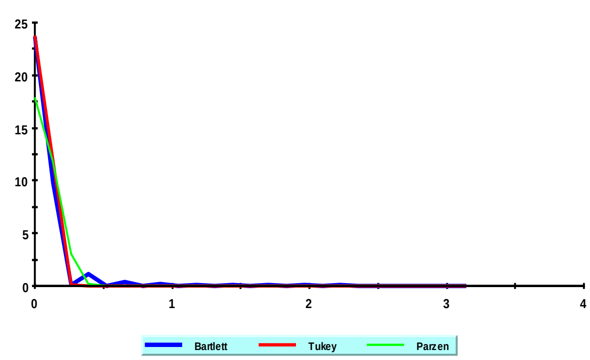
Various estimates of standardized spectral density of RESSOUTH



Various estimates of standardized spectral density of RESUSD

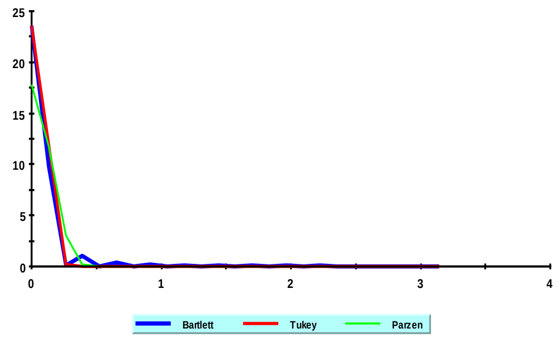


Various estimates of standardized spectral density of RESWEST

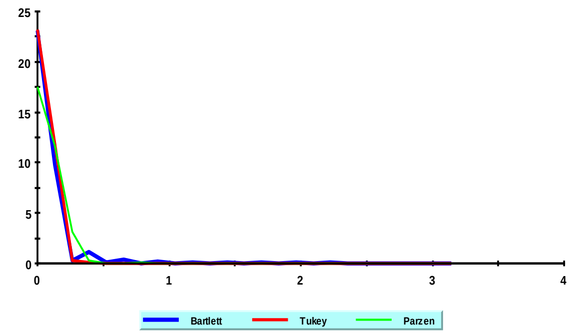


IV: Ghana with all other markets – global, regional, and foreign exchange

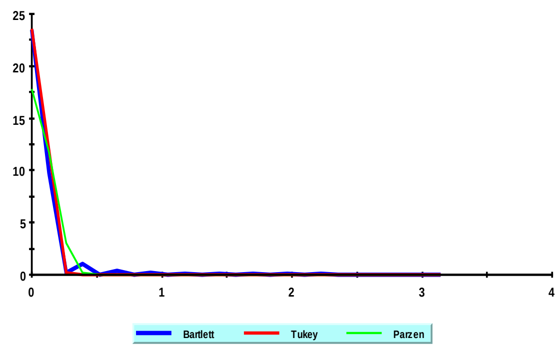
Various estimates of standardized spectral density of RESBCOM



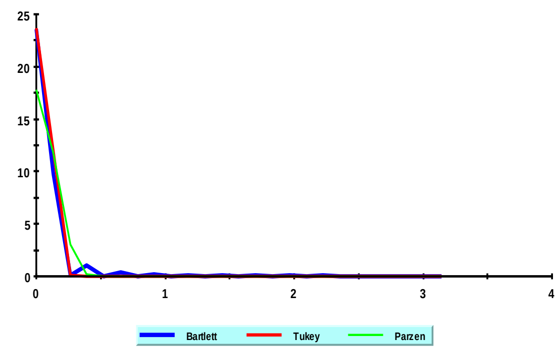
Various estimates of standardized spectral density of RESEAST



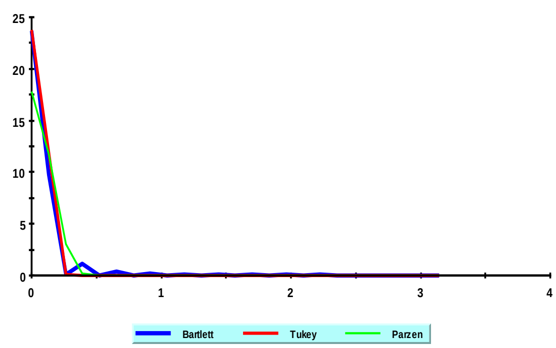
Various estimates of standardized spectral density of RESMSCIDW



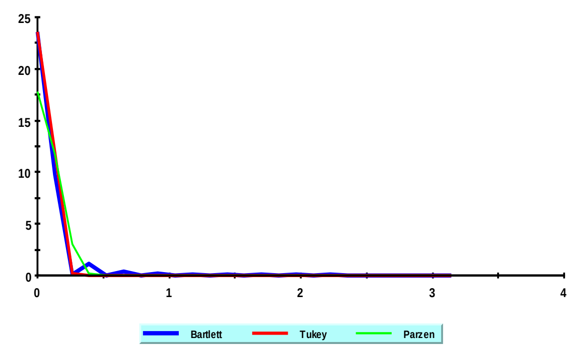
Various estimates of standardized spectral density of RESMSCIEM



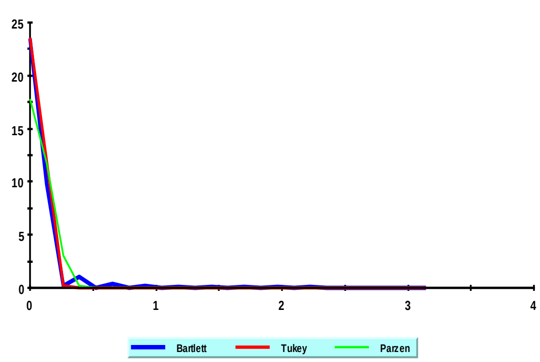
Various estimates of standardized spectral density of RESNORTH



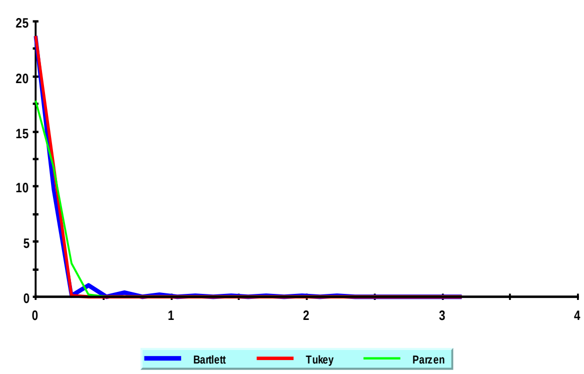
Various estimates of standardized spectral density of RESSOUTH



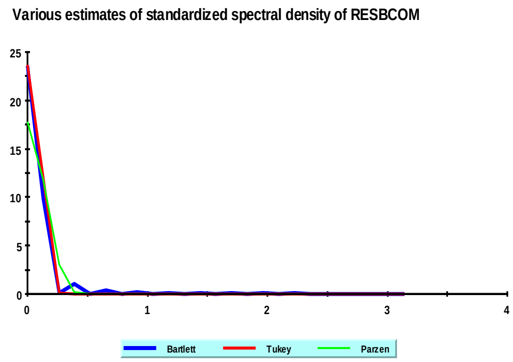
Various estimates of standardized spectral density of RESUSD

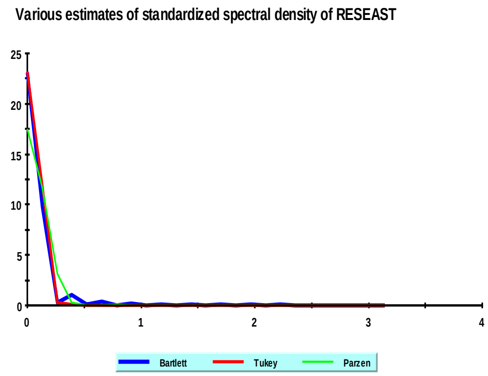


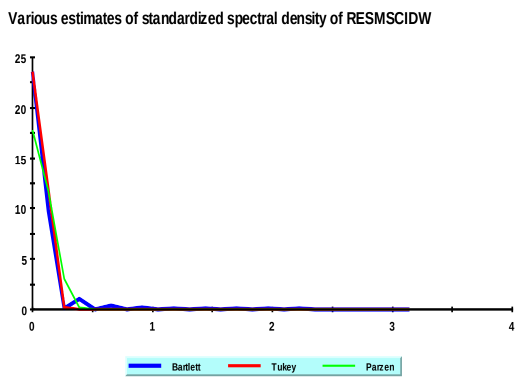
Various estimates of standardized spectral density of RESWEST

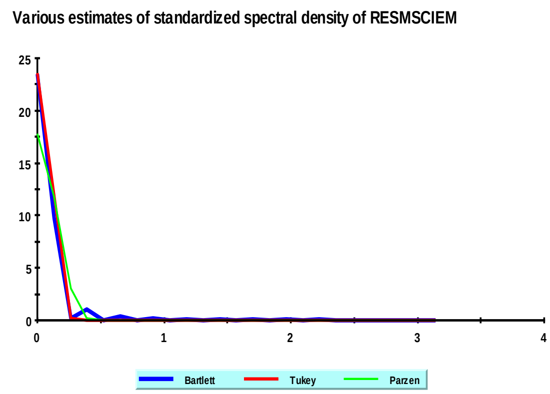


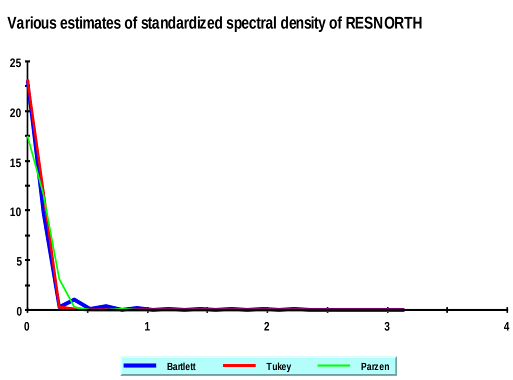
V: Nigeria with all other markets – global, regional, and foreign exchange

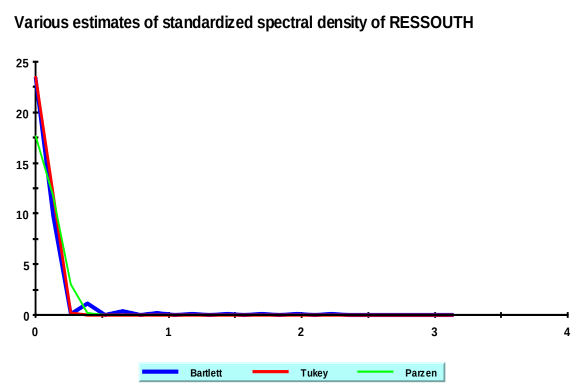


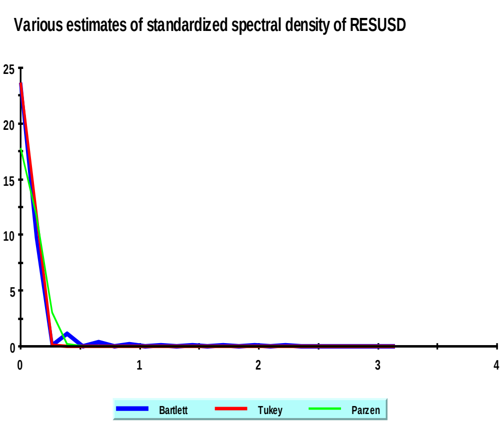


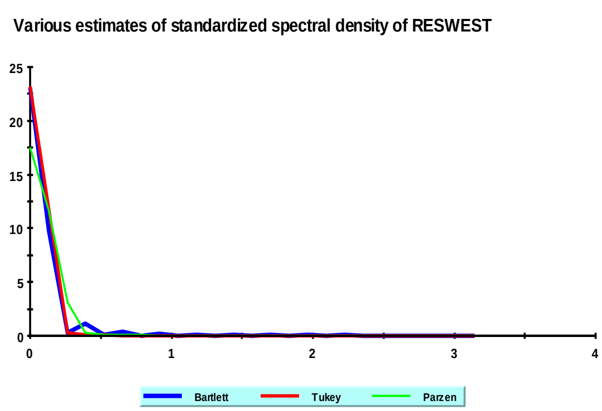






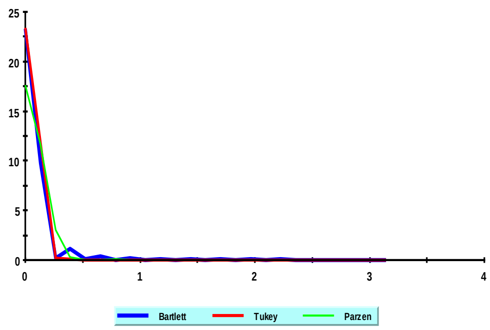




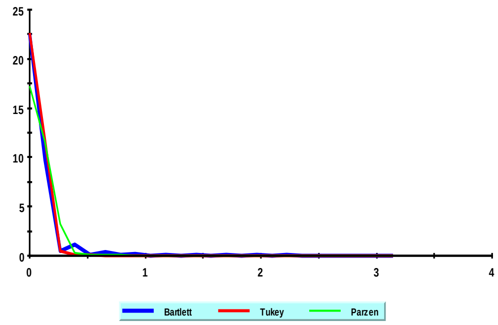


VI: Botswana with all other markets – global, regional, and foreign exchange

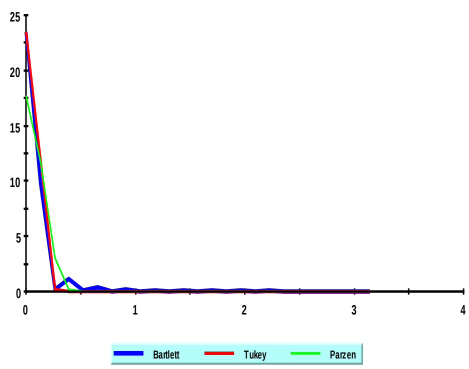
Various estimates of standardized spectral density of RESBCOM



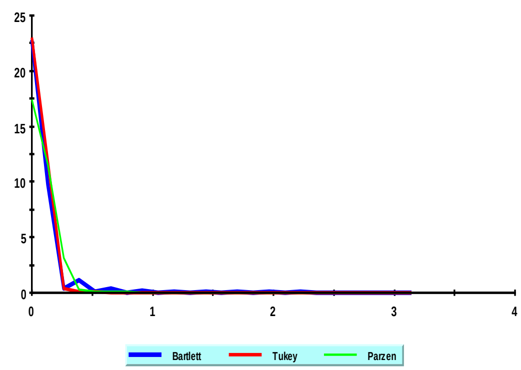
Various estimates of standardized spectral density of RESEAST



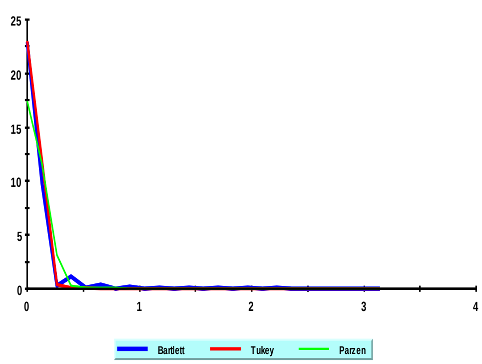
Various estimates of standardized spectral density of RESMSCIDW



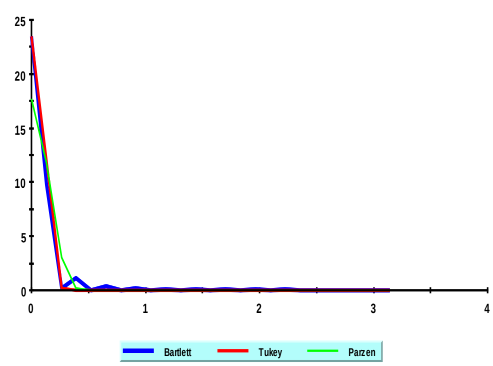
Various estimates of standardized spectral density of RESMSCIEM



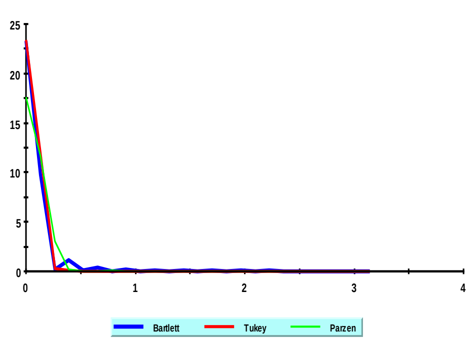
Various estimates of standardized spectral density of RESSOUTH



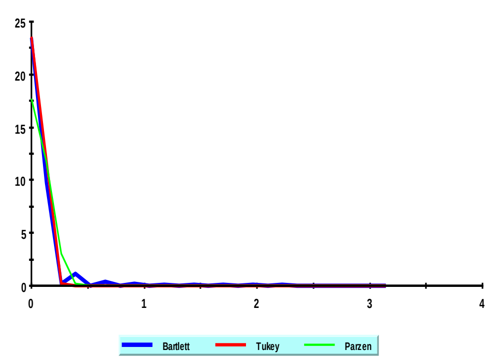
Various estimates of standardized spectral density of RESUSD



Various estimates of standardized spectral density of RESWEST

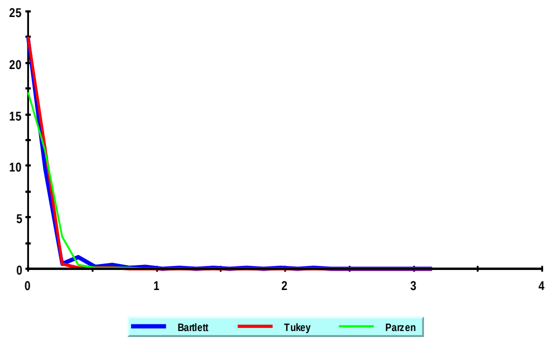


Various estimates of standardized spectral density of RESNORTH

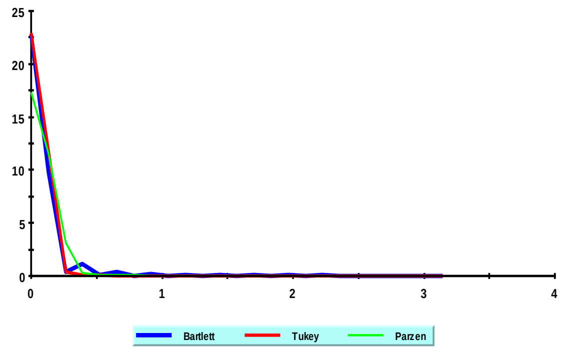


VII: South Africa with all other markets – global, regional, and foreign exchange

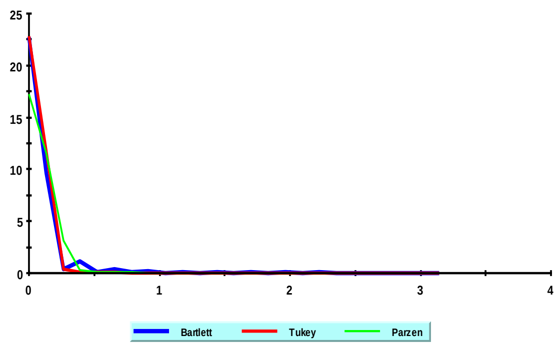
Various estimates of standardized spectral density of RESBCOM



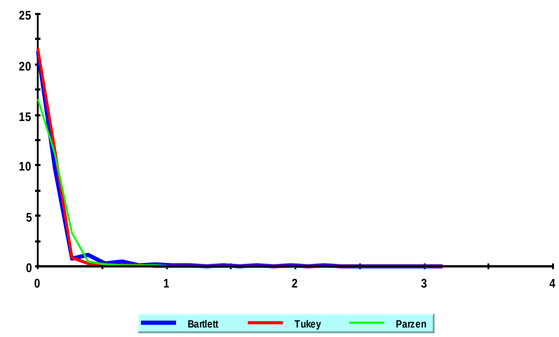
Various estimates of standardized spectral density of RESEAST



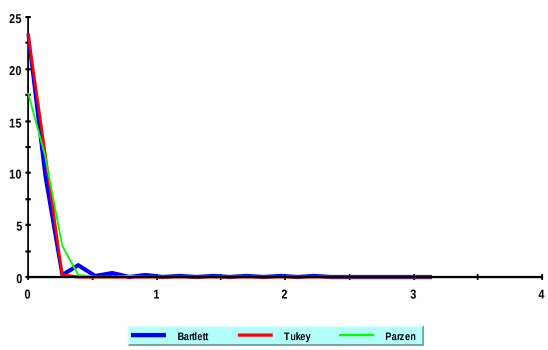
Various estimates of standardized spectral density of RESMSCIDW



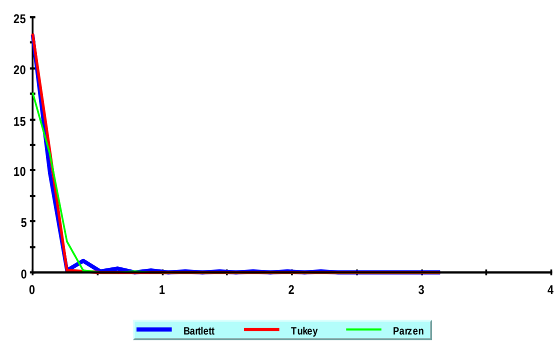
Various estimates of standardized spectral density of RESMSCIEM



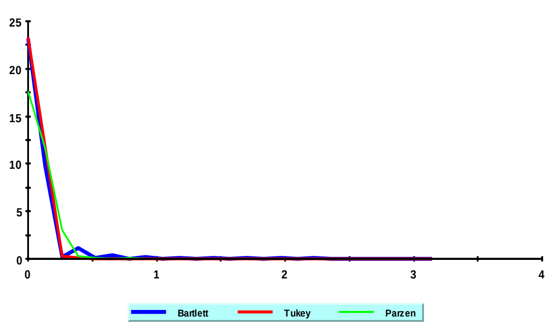
Various estimates of standardized spectral density of RESNORTH



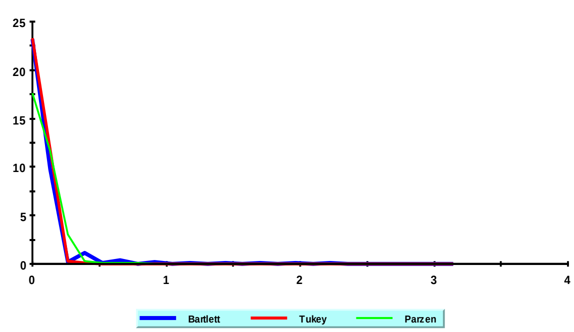
Various estimates of standardized spectral density of RESSOUTH



Various estimates of standardized spectral density of RESUSD



Various estimates of standardized spectral density of RESWEST



Appendix 4B: OLS estimates for multiple break effects

Eqn:

$$Af_{(stock)t} = \beta_1 dum(MSCI-DW)_t + \beta_2 dum(MSCI-EM)_t + \beta_3 dum(BCOM)_t + \beta_4 dum(NA)_t + \beta_5 dum(EA)_t + \beta_6 dum(SA)_t + \beta_7 dum(WA)_t + \varepsilon_t$$

Markets	β_1	β_2	β_3	β_4	β_5	β_6	β_7	R^2	dw
Botswana	0.002	0.000	0.001	0.003	0.001	-0.000	-0.003	0.003	1.949
	[0.424]	[0.001]	[0.203]	[0. 521]	[0.190]	[-0.003]	[-0.499]		
Ghana	-0.002	0.003	-0.003	0.007	-0.002	0.002	0.001	0.001	1.747
	[-0.389]	[0.486]	[-0.592]	[1.192]	[-0.343]	[0.371]	[0.129]		
Kenya	0.001	-0.002	-0.003	-0.003	0.001	-0.004	-0.006	0.001	1.303
	[0.140]	[-0.432]	[-0.588]	[-0.620]	[0.145]	[-0.875]	[-1.128]		
Morocco	-0.003	-0.007	-0.001	-0.004	-0.002	-0.002	0.004	0.001	1.480
	[-0.591]	[-1.299]	[-0.219]	[-0.680]	[-0.381]	[-0.406]	[0.537]		
Nigeria	0.002	0.003	0.001	-0.003	-0.001	-0.003	-0.002	0.000	1.290
	[0.305]	[0.618]	[0.178]	[-0.437]	[-0.235]	[-0.581]	[-0.242]		
South Africa	-0.003	0.003	-0.004	0.002	0.001	-0.000	-0.010	0.001	1.610
	[-0.303]	[0.392]	[-0.503]	[0.218]	[0.136]	[-0.055]	[-1.112]		
Tunisia	-0.001	-0.001	-0.002	0.003	0.005*	0.001	-0.004	0.002	1.496
	[-0.410]	[-0.440]	[-0.809]	[0.122]	[1.915]	[0.360]	[-1.109]		
Egypt	-0.003	-0.007	-0.001	-0.004	-0.002	-0.002	-0.004	0.001	1.480
	[-0.591]	[1.299]	[-0.219]	[-0.680]	[-0.381]	[-0.406]	[-0.537]		

Notes: ** denote statistical significance at the 5% level. Dum – dummy; NA, EA, SA, and WA are respectively, North Africa, East Africa, Southern Africa, and West Africa; Af – African stock markets; dw – Durbin-Watson statistic.*

CHAPTER FIVE

Spillover Effects, Financial Contagion, and Market Interdependence

5. Introduction

Most African countries are still poor, and financing domestic expenditures is often constrained by inefficient and narrow tax bases. Consequently, financing development has often concentrated on domestic and/or foreign borrowing. While the former has severe implications of crowding out private investments among other distortions, the latter is either subject to sudden reversals and /or comes with strings attached, and at times does not find most African countries as conducive enough. At the same time, evidence suggests that well-functioning stock markets can help mobilize capital for domestic firms. They can also help inject more liquidity into national economies to enhance growth and development. Research on the role of Africa's domestic stock markets in contributing to the continent's growth spurt is, however, very scanty. This deficiency, in part, may be due to the relatively small sizes of some of the markets, lack of information on the relative potentials of African stock markets in general and their capacity to provide decorrelation with global/developed markets during extreme conditions. Additionally, problems of continual depreciation of domestic currencies of most African economies have been noted as a major contributory factor driving away most international portfolio investors from Africa. This is because financial and portfolio managers worldwide operate on the notion that foreign exchange risk is non-diversifiable (Kodongo and Ojah, 2011), and that markets with high currency pricing may not offer optimal risk-return trade-offs.[55]

The attitude of international portfolio investors to shy away from markets with unstable domestic currencies is partly accounted for by the strong interconnectedness between stock markets and exchange rates. As opined by the international flow-oriented model of exchange rate determination, a fall (rise) in domestic currency levels enhances (reduces) the competitiveness of export-based local firms and their cash flows, which in turn increases (reduces) their trade and foreign currency current accounts balances, with the corollary effect of increasing (reducing) domestic stock prices (see Dornbusch and Fischer, 1980; Aggrawal, 1981; Koulakiotis *et al.*, 2015). Analogously, the portfolio balance theory (see *e.g.* Frankel, 1983; Tsai, 2012) posits that a well-functioning local bourse may attract foreign capital flows causing an increase in demand for domestic assets and currency, and

[55] A risk source is said to be priced if it commands a premium in the financial markets

vice versa. Increasing aggregate demand for domestic currency relative to a foreign counterpart revalues the domestic currency. This strong linkage, coupled with the continual instability in the exchange rate markets have engendered many international asset pricing models to incorporate currency risk as an important systematic factor affecting international asset returns, especially after the Bretton Woods (Kodongo and Ojah, 2011).[56] Although, the empirical literature and theoretical arguments favouring the pricing of exchange rate risk in stock returns appear conventional (see for example, Alagidede *et al.,* 2011; Chkili *et al*., 2011; Kodongo and Ojah, 2011; Md. Mahmudul *et al*., 2011; Koulakiotis *et al*., 2015, Boako *et al.,* 2016), albeit mixed empirical evidence, the dearth of related studies in emerging economies (including nascent markets in Africa) cannot be overlooked. Meanwhile, owing to frequent fluctuations in global equity markets, diversifying across emerging markets is increasingly becoming a necessity. In this vein, shedding more light on the dynamic nexuses between exchange rates and stock returns, and among stock returns will hold important implications for investors and policy makers alike.

This chapter seeks to examine the price effects of currency risk and developed stock markets in equity investments in Africa, with particular emphasis on co-movement, dependence, and (extreme) downside spillovers. Further, the chapter seeks to highlight African stock markets potential to act as viable investment alternatives for international portfolio investors, both in tranquil and turbulent times. Practically, we attempt to find answers to the following questions: *Do exchange rate and developed equity markets price risks contain information that may inform the decisions of international equity portfolio investors? Do stock markets have discernible influence on each other, and on the dynamics of foreign exchange rates, and vice versa? Are there spillover effects from exchange rates and developed equity markets to African stocks during extreme market conditions? Is there an evidence of 'shift-contagion' in African stock markets?* A key argument for the last question is that, considering the low levels of integration, liquidity, and degree of international investors' participation in African stock markets, the 'shift-contagion'[57] theory proposed by Forbes and Rigobon (2002) may not be entirely tenable for Africa. To the extent that the study reveals the strength of African stocks in cushioning international portfolio investors against foreign exchange price risks and global stock market crashes during bear and bull markets, the chapter helps to decay

[56] For example, the International Capital Asset Pricing Model (ICAPM) proposes that the covariance of assets with currency returns should be a priced factor in a world where purchasing power parity is violated (e.g., see Adler and Dumas (1983), Solnik (1974).

[57] The 'shift-contagion' theory talks about increases in cross-market correlations during crisis – see sub-sequent sub-sections for details.

doubts in the minds of investors on the perceived lack of capacity of the continent's stocks to yield higher expected risk-return trade-offs during global market sell-offs.

The contributions of the chapter to extant literature are as follows. First, despite the conventionality of related studies, not until Reboredo *et al.,* (2016), no study had analyzed co-movement and the dependence structure between stock markets and exchange rates, and among stock markets with particular focus on the impact of tail-spillover effects in exchange rates or developed stock markets on the extreme risks of emerging stock markets, and vice versa. The following studies are however, notable in the literature on tail dependence but not extreme cross-market spillovers between stocks and exchange rates, and among stock markets. Ning (2010) investigates the dependence structure between equity and the foreign exchange markets by using copulas for US, UK, Germany, France and Japan and find evidence of significant symmetric upper and lower tail dependence among the markets, with the dependence remaining significant but weaker after the launch of the euro. Using the Symmetrized Joe-Clayton (SJC) copula function to examine the dependence structure between real Canadian stock returns and real USD/CAD exchange rate returns, Michelis and Ning (2010) find significant asymmetric static and dynamic tail dependence between the real stock returns and the real exchange rate returns, such that markets are more dependent in the left than in the right tail of their joint distribution. Lin (2011) estimates the tail dependence between stock index returns and foreign exchange rate returns for five East Asian economies (Hong Kong, Indonesia, South Korea, Singapore, and Taiwan) using copulas. The results are that, for the two developed economies (Hong Kong and Singapore), there exists neither lower nor upper tail dependence between stock index returns and exchange rate returns for the period under examination. The three emerging markets, Indonesia and South Korea have much stronger lower tail dependency than right tail, indicating higher probability of double loss than a double gain. Taiwan has symmetric tail dependence with similar upper and lower tail coefficients. In Africa, Boako *et al.,* (2016) apply the Bayesian quantile regression and causality techniques to examine extreme dependence and/or interdependence between the Ghana stock market returns and returns of six exchange rate pairs using data of daily periodicity from January 4, 2011 to July 31, 2014 and find the existence of high tail dependence of the equity market on the foreign exchange market in Ghana, and that the link between the two markets supports the international flow-oriented model more than the portfolio balance theory.

In the stock market to stock market linkages literature, Bhatti and Nguyen (2012) examines the tail-dependence between the Australian financial market and other selected international stock markets using time-varying copulas and find evidence of dependence between equity markets. Similarly, Aloui *et al.,* (2011) examines the extent of the 2007-2009 global crisis and the contagion effects it induces by conducting an empirical investigation of the extreme financial interdependences of some selected emerging markets with the US using copulas. Their empirical results show strong evidence of time-varying dependence between each of the BRIC markets and the US markets, but the dependency is stronger for commodity-price dependent markets than for finished-product export-oriented markets. Other related studies include Mendes and Souza (2004), Ane and Labidi (2005), Hu (2006), among others.

Knowledge of extreme dependencies between stocks and exchange rates, and among stock markets is of significant importance to policy makers and investors seeking to shield a diversified portfolio against adverse effects of extreme market movements (Reboredo *et al.,* 2016). In line with Reboredo *et al.,* (2016) therefore, this chapter examines co-movement and downside risk spillovers among stock markets and, stock market and foreign exchange rate returns. We do this by examining the margins of stock and exchange rate markets return distributions and test for both the degree and type of their dependence at extreme levels. We model the bivariate dependence and spillover structure among stock prices, and stock prices and exchange rates in Africa using time-invariant and dynamic copulas, to analyze both average movements across marginal and joint lower- and upper-tail risk movements. Based on the copulas, we then compute the extreme conditional value-at-risk (CoVaR) in the two markets (stocks and exchange rates) to assess the downside spillover effects across them. By so doing, we uncover how large downside price movement for one market affects the stability of the other, conditional on the fact that the other market is under financial distress, as captured by its value-at-risk (VaR). Prior to that, we estimate a univariate GARCH model with leptokurtic innovations to account for asymmetry and fat-tails. Thus, while the fitted GARCH-type model helps to filter returns of both the stock markets and exchange rates and draws their marginal distributions, the extreme value copulas help to model their bivariate dependence structure and spillover effects. The copulas, unlike conventional linear regression models are able to model both the tail dependence and asymmetric tail dependence. We carry out the test for spillover effects by analyzing the significant differences between conditional and unconditional value-at-risk values using the Kolmogorov-Smirnoff (KS) bootstrap technique (Abadie, 2002).

Second, we examine the causality between exchange rate and stock markets, and among stock markets for evidences of markets interdependences using the Toda-Yamamoto causality test. Understanding how markets are interrelated could help policy makers and national governments to device strategies on best means to enhance the performance of one, contingent on the other. For instance, in examining the causality between six foreign exchange rates and the Ghana stock market, Boako *et al.*, (2016) find evidence of unidirectional causality running from stock prices to exchange rates and recommend that governments could use the equity market as a vehicle to alleviate currency crisis – see also, Kaminsky and Reinhart (1999). The causality analysis will also help us to establish whether or not the currency-stock market nexus in Africa supports the portfolio balance theory or the international trade-oriented model.

5.1 Literature survey

5.1.1 The stock - foreign exchange rate market nexus – theory and empirics

Extant literature presents two views on the dynamic linkages between stock returns and exchange rates: the international trading/flow effect and portfolio balance theory. The international trading effect theory (see Aggrawal, 1981; Koulakiotis *et al.*, 2015; Moore and Wang, 2014) suggests that a fall in domestic currency levels enhances the competitiveness of export-based firms, which in turn increases their trade and foreign currency current accounts balances. Thus, currency depreciation results in more foreign inflows into domestic stock markets. Since the value or price of a stock is the discounted present worth of the stock's expected future cash flows, stock prices will ultimately respond to the increases in expected cash flows. Thus, stock prices respond in reverse direction to a fall in domestic currency. On the other hand, the portfolio balance theory, otherwise referred to as 'stock-oriented' model (see *e.g.* Frankel, 1983; Branson, 1983; Tsai, 2012; Ho and Huang, 2015) suggests that exchange rates are determined by market mechanisms. A highly performing local stock market may attract foreign capital flows causing an increase in demand for domestic assets and currency, and vice versa. Increasing aggregate demand for domestic currency relative to a foreign counterpart revalues the domestic currency. The channel through which this can occur may either be direct or indirect (Chkili *et al.*, 2011; Koulakiotis *et al.*, 2015). In the case of the direct channel, suppose domestic stock markets begin to boom, international equity investors will suddenly increase their portfolio holdings in the local market while selling foreign assets. This has the consequential effect of causing the domestic currency to rise in value. On the other hand, the indirect channel operates through the interplay among stock market wealth, demand for domestic assets and interest rates (Chkili *et al*., 2011). Thus, increases in domestic equity assets lead to increases in wealth of domestic investors. The wealth effect then increases the demand of domestic investors causing interest rates to rise. The higher interest rates will in turn lead to increased foreign demand for domestic currency to purchase new domestic assets, thereby appreciating the domestic currency, all things being equal. Although, a number of studies have deeply examined the dynamic linkages between exchange rates and stock prices, not much is seen in Africa. Among the countries that have received much attention in this area of research are the North and Latin American economies (see *e.g.* Aggrawal, 1981; Diamandis and Drakos, 2011). Other studies have also focused on some developed and emerging Asian and BRICS (Brazil, Russia, India, China and South Africa) markets (*e.g.* Zhao, 2010). Katechos (2011) and Ulku and Demirci (2012) are among the few works that can be found in Europe. In Africa, Md. Mahmudul *et al*. (2011) for South Africa and Adjasi *et al*. (2011) for Tunisia, report that equity prices have long-run joint movement with exchange rates for the periods studied.

However, in their assessment of the impacts of exchange rate volatility on the Johannesburg Stock Exchange, Mlambo *et al*. (2013) found a weak link between the two and recommended that the South African government can use exchange rates as a policy tool to attract foreign portfolio investment. In testing the validity of the Uncovered Equity Parity (UEP) for 43 countries including South Africa, Cenedese *et al*. (2015) observe a systematic violation of the UEP – implying a disjoint between exchange rate movement and expected equity market returns differentials. The nature and extent of co-movement between exchange rates and stock prices is seen to vary across different regimes. For instance, in the application of a regime-switching model to examine the dynamic linkages between the exchange rates and equity returns of the BRICS countries, Chkili and Nguyen (2014) establish from a univariate analysis that stock returns evolve according to a low volatility regime and a high volatility regime. However, on the basis of a switching vector autoregressive (VAR) models, the influence of stock markets on exchange rates was found to be high in both tranquil and crisis periods. In a related study, Chkili *et al*. (2011:272) provide evidence to the 'effect that the relationship between stock and foreign exchange markets is regime-dependent and stock price volatility responds asymmetrically to events in the foreign exchange markets.' On the theoretical front, some studies support the international trading effect theory (*e.g.* Alagidede *et al*., 2011), and others back the portfolio balance theory. In the case of the former, Abdalla and Murinde (1997) found that exchange rates are leading indicators for stock prices for India, South Korea and

Pakistan. Liu and Wan (2012) found at best unidirectional causality from exchange rates to stock markets in China through the application of linear and non-linear causality tests to daily data from July 22, 2005 to July 15, 2011. Chkili *et al.* (2011) used a Markov-switching Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model to investigate the dynamic linkage between stock price volatility and exchange rate changes for four emerging countries from 1994 to 2009, and established that foreign exchange rate changes have a significant impact on the probability of transition across regimes.

In the case of the portfolio balance theory, Kanas (2000) observed evidence of symmetric spill-over effects from stock returns to exchange rate changes for the UK, USA, Japan, France and Canada, except Germany. Similarly, Granger *et al.* (2000) suggested that stock prices and exchange rates have inverse correlation for the Philippines. The conclusion by Phylaktis and Ravazzolo (2005) is that there is a positive relationship between stock markets and foreign exchange markets. The authors' application of cointegration and Granger causality tests on some Pacific-Basin countries during the periods from 1980 to 1999 further reveals that the stock market acts as the channel for the nexus and that the linkages are not found to be dependent on foreign exchange restrictions. This is corroborated by Diamandis and Drakos (2011). The latter's analysis of short- and long-run co-movements between stock markets and foreign exchange markets for Argentina, Chile, Brazil and Mexico, alongside the U.S. equity markets, reveals a positive relationship between the two markets of the studied economies, and finds that the stock market acts as the conduit for the linkages. In the midst of varying views on the portfolio balance theory and international trade-oriented models, several other studies have failed to establish the existence of any significant relationship between stock prices and exchange rates (see *e.g.* Chow *et al.*, 1997; Griffin and Stulz, 2001). In Africa, studies on the exchange rate-stock prices nexus appear scanty. Those of Alagidede *et al.,* (2011), Kodongo and Ojah (2011), Boako *et al.,* (2016), Md. Mahmudul *et al.* (2011) for South Africa, and Adjasi *et al.* (2011) for Tunisia are however notable. Despite this, the nature and extent of the nexus between equity prices and exchange rates, their tail-dependences, and extreme (downside) spillover effects, as well as their implications for investment decisions remains unexplored.

5.1.2 Empirics on contagion and markets interdependence

The growing body of financial literature examining contagion, integration, and interdependence of markets focus on "synchronization" and co-movements of real sectors of economies and businesses.

For example, Forbes and Chinn (2004) and Kose *et al.,* (2008) establish that financial market integration affects cross-country linkages in output, consumption and investments. In a related fashion Alagidede (2008) explain the linkages relative to country-specific characteristics and particular metrics of integration such as portfolio balancing and international risk sharing. Before these, the earlier work of Krugman (1991) established that business cycles can be more synchronized among countries with similar production structures; and that vertical integration is relevant in the synchronization of business cycles (Kose and Yi, 2001). Unfortunately, Forbes and Chinn (2004), Kose *et al.,* (2008) and Alagidede (2008) failed to shed light on the positions earlier taken by Krugman (1991) and Kose and Yi (2001). Ncube *et al.,* (2014, p.4) crowns the discussion by asserting that "intra-regional and intra-African trade with fast growing economies, together with geographically diversified trade linkages, can strengthen the capacity to absorb global shocks."

Louis *et al.,* (2009) puts the impact of the global financial crisis (GFC) into three: financial market contagion, foreign exchange markets crisis, and effects on commodity markets. They opine that contagion had always been widespread due to markets integration and diversification of assets across countries. However, despite the proposition by the decoupling theory that Africa offers better diversification opportunities during crisis, Louis *et al.,* (2009) indicate that the financial markets in Africa were affected by the contagious effects of the crisis; and that, the effects were enlarged by over-valued equities and inadequate diversification of same in the pre-crisis period. The authors' analysis however, was not based on empirical test but merely trend analysis and patterns. Moreover, the analysis fails to capture the extended periods of the 2007-2009 and Eurozone crisis.

Quite a significant number of studies also examine asset market co-movement during financial crisis. Most of these studies have dwelt on "contagion" and interdependence. A greater number of literature attempts to examine the dependence structure and the channels of shock transmission and repercussions between emerging stock markets and influential global factors. For instance, in examining financial market interdependence between the U.S and the BRIC, Aloui *et al.,* (2011) established robust proof of time-varying reliance between both markets. Mensi *et al.,* (2014) report that the BRICS equity markets show dependence with the global stock and commodity markets. Stolbov (2014) however, finds signs of decoupling in the sovereign credit default swaps (CDS) market and backs the view that Eurozone crisis had a minor non-EU effect on the BRICS markets.

Unlike emerging economies such as the BRICS, empirical studies investigating the contagion and interdependence between African equity markets and global shocks appear scanty and mixed. For example, whereas Forbes and Rigobon (2002) find no sign of contagion to South Africa, Daryl and Biekpe (2002) discover proof of contagion from the 1997 Asian crisis to South Africa, Egypt, Namibia, and Morocco despite differences in time period and hypothesis in the two studies. The dynamics is further complicated by the work of Giovannetti and Velucchi (2013). Applying the Multiplicative Error fully intra-dependent model (MEM) on some selected African markets and the U.S, UK and China, the authors reveal evidence in support of the decoupling theory and some evidence in denial. The authors conclude that whiles Kenya and Tunisia are "net creators" of volatility spill-overs from global markets to Africa; South Africa turns out to be a "net absorber". In a related setting, Alagidede (2008) reveal that apart from South Africa, African markets respond to domestic rather than global information. Hussain *et al.,* (2002) report that Africa's exports and growth rate appear to suffer similar effects from global crisis. Thus, African economies having negative (positive) export effects from global crisis also witness negative (positive) growth rates. Senbet and Gande (2009) contend that Africa's equity wealth has been greatly undermined by the GFC. And that, when this happened, well integrated markets usually got hit first. However, even those which were weakly integrated could not be completely insulated due to contagion through the real sector. The real sector diffusion of shocks manifest itself in the plummet of exports and commodity prices owing to the drop in global demand, shrinkage in foreign direct investments and portfolio inflows (Senbet and Gande, 2009).

Again, existing literature remains inconclusive on whether the transmission of shocks from large open economies to Africa is purely through the stock markets. Using the Structural VAR approach Ncube *et al.,* (2012) established that, among other channels, financial shocks from the U.S are propagated to South Africa through its equity market. However, the earlier work of Mackowiak (2007) contradicts that of Ncube *et al.,* (2012). According to the former, monetary shocks in U.S had no impact on emerging markets relative to other kinds of shocks; and that where some shocks were transmitted the conduits were short-term interest rates and exchange rates but not stock markets. The differences in results from various studies reveal the gaps in existing literature, and this underscores the need for conducting this research to discover the implications that transmission of global shocks sustain for Africa in terms of international asset allocation, market integration, and portfolio diversification.

5.1.3 Theoretical literature - contagion and/or interdependence

In spite of its popularity, ragging contentions abound on the precise definition of contagion in the financial economics literature. However, results of empirical findings on contagion would be meaningless unless theoretical and empirically relevant and better comprehension of the channels of shock transmission between and among markets is established (Pritsker, 2000).

Common theoretical definitions of contagion in the literature are primarily based on the "pure" and "fundamental-based" concepts. The former asserts that contagion is said to occur when shock is transmitted from one country/market to another, without any idiosyncratic disorders and factors. On the other hand, the fundamental-based theory defines contagion as having occurred when shock transmission is propagated from one country/market to the other through the real sector (such as trade linkages or interdependence) or macro-economic factors. If for instance, returns (*r*) on a country's (say *i*) equity markets are dependent on some set of economic factors (*f*) and a residual component or stochastic term, ε_i :

$$r_i = \delta_i + \lambda_i f + \varepsilon_i \qquad [5.0]$$

then, on the assumption that the residual component (ε_i) in Equation [5.0] shows significant correlations across markets, contagion may be deemed to have occurred, according to the fundamental-based theory (see Pritsker, 2000; Bekaert *et al.,* 2005).

Despite the dominance of the fundamental-based theory over the pure one, the former has come under severe criticisms. Pritsker (2000) argues that, the fundamental-based definition is flawed on two grounds. First, since the right set of fundamentals might not be accounted for, establishing contagion can always be questionable. The second identified shortfall is the cross-market hedging-see Pritsker (2000).

In their attempt to overcome the shortfalls inherent in the above theoretical definitions, Forbes and Rigobon (2002), hereafter referred to as FR proposed the "*shift-contagion*" theory – *significant surges in cross-market nexus during crisis.*[58] In case only linkages occur with no significant increases in cross-

[58] The understanding of the underlying orientation of this theory is a focus on the period in which the shock occurs (i.e. crisis periods). For instance, in analyzing empirically the Asia crisis in 2002, FR considered the month just after the fall of the Hang Seng stock market that occurred on October 17, 1997.

market linkages, they describe the event as *interdependence*. Their choice of the term "shift-contagion" other than contagion is exemplified in its ability to show that contagion arises from a shift in cross-market linkages, and also remains open on the manner in which the shift occurs. Their view is supported by Celik (2012) who examined the existence of financial contagion between foreign exchange markets of several emerging and developed countries during the U.S. subprime crisis and observe that unconditional correlations increase in crisis periods relative to the pre-crises period – see also, King and Wadhani (1990). In spite of what FR describe as the strengths of their shift-contagion theory, proponents of the pure contagion theory disagree and point out that, in so far as there is transmission of shocks from one market/country to the other, contagion occurs; it doesn't matter whether or not there is significant change in cross-market linkages.

A more recent advancement to the theoretical and empirical definition of contagion is that proposed by Bekaert *et al.,* (2014). The authors define contagion based on existing fundamentals as "*the co-movement in excess of that implied by the factor model"* (Bekaert *et al.,* 2014, p. 2598). Based on a benchmark factor model, called the "interdependence model"[59], Bekaert *et al.,* (2014) proposed four distinct types of contagion. They proposed that contagion emanating from the US or global financial sector be called "*US contagion" or "Global contagion*" respectively. Further, they describe increases in the joint movement of domestic portfolios during crisis relative to the factor models predictions as "*Domestic contagion"*; and finally, correlation of excess returns across equities uncorrelated to the factor model in crisis periods as "*Residual contagion*". When tested empirically, the authors retreat on some of the propositions on the types of contagion they have proposed. First, they strongly reject the interdependence model statistically. Additionally, while the authors establish significant statistical but little economic proof in favour of the US and global contagions, they find strong evidence supporting the domestic contagion. On account of the limited success rate (about 25%) of the proposition by Bekaert *et al.,* (2014) in their own empirical test, the immediate acceptance of their propositions remains an empirical question that only time can tell.

On account of the above, the inclination of this chapter is to agree with FR's shift-contagion theory, albeit with modification. We thus, argue in favour of '**delayed shift contagion'** – *thus increases in shock propagation post-crisis* (see details in sub-section 5.4.6). As a primer to our empirical test to

[59] They describe the interdependence model as the propagation of shocks proportional to the factor exposures in the tranquil period.

establish evidence of delayed shift contagion, we wish to bring to the fore some existing facts in support of the need to extend the definition from *shift-contagion* to *delayed shift-contagion*. First, using a standard factor model representation of an international CAPM framework that allows for spillover effects outside crisis periods, Dungey and Gujurel (2015) find substantially more evidence of US banking volatility spillovers to about 60% of the sample in non-crisis periods relative to the 2007-2009 crisis period. When crisis is disaggregated into phases, the authors report that volatility contagion is limited in the phase one and more prevalent in phase two. The authors' further report that evidence of systematic contagion (potential structural changes in global systematic risk exposure) is strongly skewed towards developing markets. Thus, the belief that global shocks propagation to developing markets may stagger during crisis and intensify post-crisis is not far from reality.

5.1.4 Contagion transmission pathways

Although speculations are rife on the spread of contagion due to irrational exuberance, arguments to support this are virtually non-existent. Majority of studies examining the transmission pathways of financial shocks from one market to the other have focused on the rational channels (see for example, Kodres and Pritsker, 1999; Pritsker, 2000; Bekaert *et al.,* 2014). In this sub-section, we propose critical rational channels for the transmission of contagion (particularly into emerging markets), unearth the relevant factors that oil the wheels of an emerging markets' susceptibility to contagion, and examine a theoretical framework for shock transmission.[60]

Different international finance scholars have proposed different transmission pathways for contagion. Pritsker (2000) identified real sector linkages, financial market linkages, financial institution linkages, and interactions between financial institutions and financial markets, as the possible rational conduits for contagion. Studies by Kodres and Pritsker (1999), herein referred to as KP, on the financial market component in the Pritsker (2000) rational contagion model established four different pathways of contagion. The first channel is the correlated information pathway. The intuition behind this channel is that if an observed real shock in one county is propagated to another country through real linkages, then the financial markets of the two countries will be connected. The second financial market contagion occurs as a result of market participants (say a Bank or non-bank

[60] The intent is not to empirically test for these channels but to provide a framework to spur further studies seeking to examine channels of shock transmission to African stock markets.

financial institution) diversifying portfolios across markets in response to a shock. In the parlance of Pritsker (2000), market participant's decision to diversify across markets in response to shocks may be influenced by the correlated liquidity shock theory (see also Calvo, 1999) and feedback trading.[61] The penultimate financial market contagion identified by KP is the cross-market rebalancing or cross-market hedging. KP explains this as the channel that spreads contagion when investor's responses to shocks result in the readjustment of their hedges to economic shocks. Thus, shocks can be transmitted between two countries not necessarily because they share common economic risks, but because they share risks factors with another country. The last of the channels is the one due to wealth shocks. This is the situation where investors change their asset holdings in response to shocks affecting their wealth. The striking difference between the wealth shock and correlated liquidity shock is that, in the case of the former, investors have the right but not obligation to liquidate, whereas in the later, liquidation is an obligation.

Further to KP, and Pritsker (2000), Bekaert *et al.,* (2014) examine six channels for contagion across portfolios based on how the reliance of factor exposures on various instruments varied in the wake of the 2007-2009 financial crisis. The theoretical underpinnings of these propositions are similar to the Forbes and Rigobon (2002)'s propositions based on fundamentals and the factor model approach in Bekaert *et al.,* (2005).[62] The six channels are: i). international banking sector ii). Financial policies iii). The "globalization hypothesis iv). Reduced information asymmetry v). "Wake-up call hypothesis", and vi). Global risks and liquidity indicators.[63] When empirically tested, the authors find varying results supporting or rejecting the workability of the identified channels. For instance, they find no significant evidence in favour of the globalization hypothesis; banking sector; and information flow links, as useful channels for transmitting contagion. Instead, the global risks and liquidity indicators do. Strong evidences were established for the wake-up call effects and domestic banking policies as the driving outlets of domestic contagion.

Based on the above theoretical frameworks on channels of contagion, this section outlines a hybrid conceptual framework in Table 5.0 based on the rational contagion theory (as in Pritsker, 2000); with emphasis on financial market contagion (as explained by Kodres and Pritsker, 1999); and

[61] See Pritsker, (2000)
[62] All of them define contagion based on residual co-movement over fundamentals
[63] See Bekaert *et al.,* (2014) for detailed explanations of the six channels.

incorporating some relevant channels proposed by Bekaert *et al.,* (2014), as the critical pathways through which global shocks can be transmitted to emerging/developing equity markets (example, Africa).

Assumptions (Economy): *The following assumptions are made for the proposed hybrid theoretical framework.* The regional economy (e.g. Africa, which is the shock recipient) under consideration is made up of *N* countries (indexed from $j = 1, 2, 3\ldots N$). It is assumed that each country *j* in the regional economy has domestic financial market (FM_j) representing the liquidity level of country *j.* Another assumption is that firms in country *j* willing to seek financing outside the financial markets can do so but only from either any local bank or an international bank listed on a stock exchange; and that there are *P* (indexed $s = 1,2,3\ldots P$) number of Banks ($Bank_P$) in country *j* either local or international listed on country *j*'s national stock exchange or an international stock exchange or both, or not listed at all in the case of domestic banks and can act as a licensed dealing member (LDM) or underwriter in country *j.* We also assume an economy with a set of *Q* domestic macroeconomic variables ($MAEC_Q$) in country *j.* Further, we assume that there is *K* number of global economic variables (GEV_K) in the world economy. Finally, it is assumed that there is *H* number of countries in the global economy outside the emerging market's economy, each having a financial market indexed z = 1, 2, 3… H ($NAFM_z$). The market in country *z* is assumed to have some linkages with the market in country *j* in one way or the other, at least, for the past two decades.

The framework/theoretical model in Table 5.0 can be represented in an equation as:

$$AFM_j = f(NAFM^{Z}_{z=1}, MAE^{S}_{Q=s}, BANK^{S}_{P=s}, GEF^{S}_{K=s}, AFM^{S}_{j=s}) + \varepsilon \qquad [5.1]$$

where ε is as defined in Equation [5.0]. Even though, we express the linkages in equation form, it must be emphasized that they are strictly in reduced forms, and must not be considered as a formal model.

Table 5.0: Financial Market Contagion Transmission Pathways

Category	Transmission Pathway	Type of contagion	Existing Study in Africa
1	$NAFM_z \rightarrow AFM_j$	Market to market	Daryl and Biekpe (2002)
2	$MAE_Q \rightarrow AFM_j$	Economy-wide	Ncube *et al.,* (2014)
3	$NAFM_z \rightarrow BANK_P \rightarrow AFM_j$	Market participants linked	N/A
4	$GEF_K \rightarrow MAE_Q \rightarrow AFM_j$	Global economic factor and macroeconomic interaction	N/A
5	$GEF_K \rightarrow NAFM_z \rightarrow MAE_Q \rightarrow AFM_j$	Financial market contagion via macroeconomic factors	N/A
6	$AFM_{ji} \rightarrow AFM_{jii}$	Regional	N/A

Note: N/A means not available.

The intuition behind the model in Equation [5.1] is that because most financial markets in emerging economies are generally less integrated with developed counterparts; direct transmission of shocks from the latter to the former may be rare. Instead, shock propagation may occur through other channels and economic agents. Therefore, estimating spillover effects from developed markets (i.e. idiosyncratic shocks as proposed by Dungey and Gajurel (2015)) from the stock-stock perspective may be necessary but insufficient. Hence the need to consider other factors as proposed in Equation [5.1].

5.2 Data and empirical strategies

5.2.1 Data

The empirical analysis of spillover effects, contagion, dependence and interdependence is conducted using weekly data from 10th January, 2003 to 12th February, 2016 with the free float-adjusted market capitalization Morgan Stanley Capital International (MSCI) indices of a set of six (6) African stock markets (namely, Kenya, South Africa, Morocco, Nigeria, Botswana, and Egypt), the Euro (EUR) and United States of America dollars (USD) foreign exchange rates against domestic African currencies[64], as well as four developed equity markets (namely, Asia-excluding Japan (Asia-ex. J), FTSE 100, S&P500, EUSTXX50). All sampled African economies are opened to foreign capital

[64] The following domestic currencies against the EUR and USD are used: South Africa (Rand), Egypt (Pound), Kenya (Shilling), Nigeria (Naira), Botswana (Pula), and Morocco (Dirham).

flows and have taken the path of reducing foreign exchange and capital controls; and thus becoming highly relevant in international investor portfolios. The nexus between stock markets in these countries and developed markets, as well as, the foreign exchange market requires special focus in terms of overall portfolio and risk management. We use the EUR and USD as the foreign exchange rate pairs against the domestic currencies because they virtually dominate most commercial and financial transactions in these economies. All currencies are computed into quantities in the foreign currencies (EUR and USD) per the prevailing rates. Thus, an increase (decrease) in the exchange rates signifies a quantum of appreciation (depreciation) of the value of the local (African) currency. Similarly, the stock markets datasets (Africa and developed) are expressed in USD for ease of comparison. Except Botswana (which is sourced from DataStream), all other data are gleaned from Bloomberg and analyzed with their returns computed as the logarithmic difference between two consecutive series. To examine contagion around the 2007-2009 global financial crisis (GFC), we disaggregate the dataset into pre-, during-, and post-crisis periods– details to be outlined in subsequent sections.

5.2.2 Modelling dependence using copula

Though different approaches exist for measuring dependence, the copula application appears to have gained more popularity due to its superiority over other traditional methods (see for example, Delatte and Lopez, 2013; Reboredo and Ugolini, 2015; Reboredo *et al.,* 2016; Pourkhanali *et al.,* 2016). Among the many usefulness of the copula is its ability to provide information on average dependence as well as the tails of the joint distribution based on the marginal models of the distribution – see more on copula in Joe (1997) and Nelsen (2006). These attributes of the copula make it more robust compared to conditional-mean or standard linear regressions and various forms of quantile estimators (either frequentist or Bayesian).[65] Whilst the standard linear regression estimators such as the ordinary least squares (OLS) only fits a single regression curve to the mean part of the response distribution in an attempt to establish relationships between the response variable and a given set of predictors, the quantile regression techniques provide information about the tails (upper and lower) and the median but do not allow separate models for the marginal distribution.

[65] For details on quantile regressions see Koenker and Bassett (1978), Baur (2013), and Boako et al., (2016).

The view of Sklar (1959) is that a multivariate distribution function has the components: marginal distributions which capture the individual characteristics of each series, and a copula that exhaustively shows the dependence between them. Moreover, a copula has the ability to link any given set of marginal distributions to construct a joint distribution, giving a great deal of flexibility in the specification of the marginal distribution and the dependence structure between them (Delatte and Lopez, 2013). Although applied in many other fields, the copula has recently been seen in the financial literature, with very little or no application in the African context.

In this chapter, we model the dependence between African stock markets, on one hand, each of the two foreign exchange rates and each of the four developed markets, on the hand in the bivariate framework using copulas. For each dependence structure, we consider two scenarios: time-invariant time-varying dependence. Principally, we are interested in capturing the probability of potential joint movement of extreme events given by high or low values.

Prior to estimating the copulas, we characterized the marginal densities of the African stock, foreign exchange rates, and developed stock market returns (r_t) with an ARMA*(p,q)* model:

$$r_t = \theta_0 + \sum_{j=1}^{p} \theta_j r_{t-j} + \varepsilon_t - \sum_{i=1}^{q} \phi_i \varepsilon_{t-i}, \qquad [5.2]$$

$\varepsilon_t = \sigma_t z_t$, and

$$\sigma_t^2 = \varpi + \sum_{k=1}^{v} \beta_k \sigma_{t-k}^2 + \sum_{h=1}^{s} \alpha_h \varepsilon_{t-h}^2 + \sum_{h=1}^{s} \lambda_h I_{t-h} \varepsilon_{t-h}^2 \qquad [5.2.1]$$

$$I_t = \begin{cases} 1 \ if \ \varepsilon_{t-h} < 0 \\ 0 \ if \ \varepsilon_{t-h} \geq 0 \end{cases}$$

where, ε_t is the real-valued discrete time stochastic process; z_t is an unobservable random variable belonging to an *i.i.d.* process (that is zero mean and constant variance); σ_t^2 is the conditional variance of ε_t with dynamics given by a threshold generalized autoregressive conditional heteroscedasticity (TGARCH) model – Equation [5.2]; *p* and *q* are non-negative integers; θ_j and ϕ_i are respectively, the autoregressive (AR) and moving average (MA) parameters. In Equation [5.2.1], ϖ is a constant; σ_{t-k}^2 captures the GARCH component; ε_{t-h}^2 is the ARCH component; and λ

captures asymmetry/leverage effects. A $\lambda > 0$ means future conditional variances will proportionately increase more following a negative shock than following a positive shock of similar magnitude. It must be noted that, when $\lambda = 0$ the volatility model in Equation [5.2.1] becomes the GARCH model.

After using the fitted TGARCH model to filter returns of all variables and drawing their marginal distributions, we then apply the extreme value copulas to model their bivariate dependence structure.

Applying Sklar's theorem (Sklar, 1959), and given two random variables x and y, with distribution function $F_{XY}(x, y)$ and with marginal functions $F_X(x)$ and $F_Y(y)$, we can express the joint distribution of y and x as a multivariate function coupling the marginal distribution functions to represent the joint distribution function:

$$F_{X,Y}(x, y) = C(F_X(x), F_Y(y)) \qquad [5.3]$$

where, $C(u, v)$ for $u = F_X(x)$ and $v = F_Y(y)$ is a (bivariate) copula function that is uniquely determined for the ranks $RanF_X \times RanF_Y$ when margins are continuous. Additionally, the joint density $f_{XY}(x, y)$ can be obtained from the copula density $c(u, v)$ as:

$$f_{XY}(x, y) = c(u, v) f_X(x) f_Y(y) \qquad [5.3.1]$$

where, $c(u,v) = \partial^2 C(u,v) / \partial u \partial v$, and $f_X(x)$, $f_Y(y)$ are respectively, the marginal densities of the X and Y variables.

The right (upper) and left (lower) tail dependence can be computed from the copula as:

$$\tau^U = \lim_{u \to 1} \Pr\left[X \geq F_X^{-1}(u) \mid Y \geq F_Y^{-1}(u)\right] = \lim_{u \to 1} \frac{1 - 2u + C(u,u)}{1 - u} \qquad [5.3.2]$$

$$\tau^L = \lim_{u \to 0} \Pr\left[X \leq F_X^{-1}(u) \mid Y \leq F_Y^{-1}(u)\right] = \lim_{u \to 0} \frac{C(u,u)}{u} \qquad [5.3.3]$$

where, $\tau^U, \tau^L \in [0,1]$. Lower (upper) tail dependence means that we have a non-zero probability of observing extremely small (large) values for one variable together with extremely small (large) values for another variable.

To analyze the dependence structure between African stock markets, on one hand, and each of the foreign exchange rates and developed equity markets on the other hand, we employ four copula specifications, namely: *Gaussian (Normal), Student's t, Gumbel, and rotated Gumbel copulas*. The corresponding models and their dependence parameters that estimate the strength of the dependence are briefly presented below; Table 5.1 shows the functional forms and properties.

1. The *normal Gaussian copula* is the most widely used in finance due to its convenient properties. It allows for equal degrees of positive and negative dependence but does not allow for tail dependence $\left(\tau^U = \tau^L = 0\right)$. It is defined by $C_N(u,v;\rho) = \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v))$, where Φ is the bivariate standard normal cumulative distribution function with correlation ρ between *X* and *Y*, and where $\Phi^{-1}(u)$ and $\Phi^{-1}(v)$ are standard normal quantile functions. A good feature of this copula is that the dependence parameter is the Pearson's correlation coefficient with the relation, $-1 \leq \rho \leq 1$.
2. The *Student's-t copula* on the other hand assumes average dependence for both lower and upper tails of the joint distribution. It is given by $C_T(u,v;\rho,d) = T_{d,\rho}(t_d^{-1}(u), t_d^{-1}(v))$, where *T* is the bivariate *student-t* cumulative distribution function (CDF) with degree-of-freedom parameter *d* and correlation ρ where $t_d^{-1}(u)$ and $t_d^{-1}(v)$ are the quantile functions of the univariate student-t distribution with degree-of-freedom parameter, *d*.
3. The *Gumbel copula* has upper tail dependence. It is given by $C_G(u,v;\delta) = \exp\{-[(-\ln(u))^\delta + (-\ln(v))^\delta]^{1/\delta}\}$. It must be noted that the bivariate variables become independent of each other when $\delta = 1$.
4. The *rotated Gumbel copula* is better suited for strongly correlated variables at low values; with the dependence parameter $\delta \in [1,\infty]$ that does not allow for negative dependence and takes a value of 1 in the case of independence. The lower tail dependence then becomes, $\tau^L = \left(2 - 2^{1/\delta}\right)$.

Table 5.1: Copula specifications

Copula	Distribution	Parameter Space	Independence	Lower tail dep	Upper tail dep
Gaussian	$C_N(u,v;\rho)=\Phi_\rho(\Phi^{-1}(u),\Phi^{-1}(v))$	$\rho\in(-1,1)$	$\rho=0$	0	0
Student-*t*	$C_T(u,v;\rho,d)=T_{d,\rho}(t_d^{-1}(u),t_d^{-1}(v))$	$\rho\in(-1,1)$ $d\in(2,\infty)$	$\rho=0$	$\mathcal{G}T(\rho,d)$	$\mathcal{G}T(\rho,d)$
Gumbel	$C_G(u,v;\delta)=\exp\{-[(-\ln(u))^\delta+(-\ln(v))^\delta]^{1/\delta}\}$	$\delta\in(1,\infty)$	$\delta=1$	0	$2-2^{1/\delta}$
Rotated Gumbel	$C_{RC}(u,v;\delta)=u+v-1+C_G(1-u,1-v;\delta)$	$\delta\in(1,\infty)$	$\delta=1$	$2-2^{1/\delta}$	0

Note: The column titled "Independence" shows the parameter values that lead to independence copula. u *and* v *denote the cumulative density functions of the standardized residuals from the marginal models and* $0\le u,v\le 1$. Φ_ρ *is the bivariate cumulative distribution of the standard normal with correlation coefficient* ρ *and* Φ^{-1} *is the inverse function of the univariate normal distribution.* $T_{d,\rho}$ *is the bivariate student's t distribution with correlation coefficient* ρ *and degree of* d*, which captures the extent of symmetric extreme dependence;* t^{-1} *is the inverse function of the univariate Student's t distribution.* δ *denotes the parameters for the Gumbel and rotated Gumbel copulas.*

Following Patton's (2006) parametric model, we allow the parameters of some copula distributions to change over time in order to account for time-varying dependence. Effectively, we characterize the temporal dynamics in the *Gaussian and Student-t* copula as an autoregressive moving average process - ARMA (1, *q*) to capture any variation in dependence as:

$$\rho_t=\wedge\left(\psi_0+\psi_1\rho_{t-1}+\psi_2\frac{1}{q}\sum_{j=1}^{q}\Phi^{-1}\left(u_{t-j}\right).\Phi^{-1}\left(v_{t-j}\right)\right) \qquad [5.3.4]$$

where $\wedge(x)=\left(1-e^{-x}\right)\left(1+e^{-x}\right)^{-1}$ is the modified logistic transformation that keeps the value of ρ_t in (-1, 1) and $\Phi^{-1}(x)$ is a standard normal quantile function that is substituted by $t_t^{-1}(x)$ for the *student-t* copula.

We estimate time-varying copula parameters for the Gumbel and rotated Gumbel based on the Generalized Autoregressive Score (GAS) model of Creal *et al.,* (2013). We assume a functional evolution of the copula parameter on its own lagged value and a "forcing variable" related to the scaled score of the copula log-likelihood. The approach uses increasing transformation (e.g. log) to copula parameters in order to ensure that parameters are constrained to lie in a particular range (e.g $\rho\in(-1,1)$). Following Patton (2012), the evolution of the transformed parameter is denoted

$$f_t=h(\delta_t)\Leftrightarrow\delta_t\Leftrightarrow h^{-1}(f_t) \qquad [5.3.5]$$

where $f_{t+1}=\theta+\beta f_t+\alpha I_t^{-1/2}s_t$ [5.3.6]

$$s_t \equiv \frac{\partial}{\partial \rho} \log c(u_t, v_t; \delta_t) \qquad [5.3.7]$$

$$I_t \equiv E_{t-1}[s_t s_t'] = I(\delta_t) \qquad [5.3.8]$$

By these expressions, the future value of the copula parameter depends on a constant, the present value, and the score of the copula log-likelihood $I_t^{-1/2} s_t$.

As stated earlier, the copula specifications allows for the decomposition of the log-likelihood function as a sum of the log-likelihood function of the marginal and the log-likelihood function of the copula – see Equation [5.3.1]. This decomposition allows us to estimate the copula and marginal density parameters. We consequently use the two-stage maximum likelihood approach. First, we estimate the parameters of the marginal distributions by maximum likelihood and then later maximize the log-likelihood function by taking the probability transform of the standardized marginal residuals u_t and v_t as pseudo-sample observations for the copula. The latter stage process helps us to estimate the copula parameters. We evaluate the performance of each copula model and also select the number of lags to be included in the mean and variance equations for each series in the marginal models based on the Alkaike information criterion (AIC) adjusted for small sample bias – see Breymann *et al.,* (2003). The best model is the one that maximizes (minimizes) the log-likelihood (Alkaike information criteria).

5.2.3 The interdependence estimator

To augment results from the copula estimates, we further examine the series to observe whether or not foreign exchange rates and the developed markets drive changes in African stock markets or vice versa. Particularly for the exchange rate-stock market nexus, this segment is necessary to help shed light on whether or not the dependence structure between the two asset classes follows the international trade-oriented model or the portfolio balance theory. Knowledge of this will aid policy makers and national governments in their policy formulations. For example, knowing for sure that booming local markets induce stability in foreign exchange rates will help most governments in Africa to use the equity market as a means to stimulate stable local currencies (see Boako *et al.,* 2016). We thus ask the question: *is there any causal link between returns of African stock markets, on one hand, and foreign exchange rates and developed equity markets, on the other hand?* A priori, we hypothesize that given Africa's recent advances in opening their markets and economies for international portfolio flows and their strides in contributing to the overall growth spurt of world equity markets, albeit slothful, bearish or bullish conditions of the local markets may influence changes in the foreign exchange rates of domestic economies, as well as developed equity markets. That said, we wish to indicate that the capacity of Africa's equity markets to affect changes in developed stock markets may not be substantial, if any. Thus, we anticipate a uni-directional causality from developed markets to African markets, and largely a bi-directional causality between African markets and the EUR and USD exchange rates, particularly the USD rate given that it is a 'de-facto' second transactional currency of most African economies.

We apply the Todo-Yamamoto - TY (1995) test instead of the widely used Standard F-type Granger (SFGC) causality test for the interdependence analysis. Because the SFGC test relies on the stationarity assumption, it usually suffers from the problem of possible spurious causality in a situation where one or both series tested are non-stationary (He and Maekawa, 2001). On account of this limitation, Toda and Yamamoto (1995) specified the augmented vector autoregressive (VAR) model approach, which is not much sensitive to stationary conditions in the VAR system. The maximum order of integration in the level series is only added to the chosen lag length, *p*, when specifying the VAR model in the level series. This augments the VAR(*p*) system to obtain a VAR(*p* + *d*max), where *d* denotes the maximum order of integration. We estimate the following bivariate augmented VAR model:

$$y_t = \varphi_1 + \sum_{j=1}^{h+d} \psi_{1j} y_{t-j} + \sum_{i=1}^{l+d} \gamma_{1i} x_{t-i} + \mu_{1t} \qquad [5.4]$$

$$x_t = \varphi_2 + \sum_{j=1}^{h+d} \psi_{2j} x_{t-j} + \sum_{i=1}^{l+d} \gamma_{2i} y_{t-i} + \mu_{2t} \qquad [5.4.1]$$

where y_t denotes individual African stock market prices; x_t represents either EUR and USD foreign exchange rates against local currencies or developed equity market prices in the level series; *h* and *l*, respectively, denote the optimal lag lengths for y_t and x_t; and μ_{1t}, μ_{2t} are the uncorrelated random error terms of the augmented VAR system. The T-Y approach uses a modified Wald test which follows a chi-square distribution with *p* degrees of freedom. From Equation (5.4), the following hypotheses are formulated:

Null hypothesis: x_t does not Granger-cause y_t, given that $\sum_{i=1}^{l} \gamma_{1i} = 0$

Alternate hypothesis: x_t does Granger-cause y_t , given that $\sum_{i=1}^{l}\gamma_{1i} = 0$

Analogously, based on the augmented VAR in equation (5.4.1):

Null hypothesis: y_t does not Granger-cause x_t , given that $\sum_{i=1}^{l}\gamma_{2i} = 0$

Alternate hypothesis: y_t does Granger-cause x_t , given that $\sum_{i=1}^{l}\gamma_{2i} = 0$

Here, a bidirectional causal relationship is obtained between x_t and y_t if the two null hypotheses for the joint test are both rejected. Moreover, we obtain a unidirectional causal relationship if one of the null hypotheses is rejected and no causal relationship if we fail to reject both null hypotheses. Evidence of no causality, uni-directional causality, and bi-directional causality will mean independence, dependence (but not interdependence) and interdependence, respectively. We check the stability/adequacy of the estimated VAR equations (for the T-Y causality tests) using the inverse roots.

5.2.4 Estimating spillovers with CoVaR-copula

We estimate downside spillovers from foreign exchange markets and developed equity markets to stock markets in Africa using downside value-at-risk (VaR). VaR converts the risk of an asset or portfolio into a single number, making it an easy to comprehend and widely used measure of the risk of financial assets. VaR also helps to quantify the maximum loss that an investor may incur within a specific time horizon and confidence level by holding a long position (downside risk) or a short position (upside risk) – Reboredo *et al.,* (2016). However, the potency of VaR in calibrating risk has been challenged by most recent studies on account that it is not sub-additive (Artzner *et al.,* 1999)[66], meaning the VaR of a combined portfolio can be larger than the sum of the VaRs of its components. Thus, not only is the VaR as a measure of risk incompatible with the Markowitz portfolio theory (Markowitz, 1952), but it does not capture the risk reduction attributes of diversification. Throughout its applications, VaR fails to take into account how much risk is

[66] A measure of risk say, σ () is considered sub-additive, if, for any two functional assets P and Q, $\sigma(P+Q)$ is not greater than $\sigma(P)+\sigma(Q)$. Thus, sub-additivity is: $\sigma(P+Q) \le \sigma(P)+\sigma(Q)$, for any risks of P and Q.

propagated from a single exposure to the economy-wide system (i.e. lacks the strength to measure systemic risk)[67] when the entire system is under stress.

With its open market policies to international investors and increased efforts at overcoming barriers to international trade, investments in African economies have increasingly become attractive to foreign investors. This makes studies on the spillover of global risks to African economies an interesting arena for both local and international investors. To examine the spillover of risk from foreign exchange and developed equity markets to African stock markets, and vice versa therefore, we consider the impact of financial distress in one market (measured by its VaR) on the VaR of another market – *that is conditional VaR*. As outlined in the systemic risk literature, risk spillover is linked to the spread/transmission of failures from one market to another.

In analyzing the systemic impact across the considered asset markets (i.e. stocks and exchange rates), we use the conditional value-at-risk (CoVaR) as populated by Adrian and Brunnermeier (2011), generalized by Girardi and Ergun (2013), and used widely by Reboredo *et al.,* (2016). In plain language, the CoVaR permits the measuring of the impact of financial distress in the foreign exchange or developed stock markets on the African stock market returns by providing information on the VaR of the stock market returns (Africa) conditional on the fact that the exchange rate and developed stock markets experience extreme conditions or are undergoing turmoil. We formulate the CoVaR model as follows:

Let y_t^s denote returns for the African stock markets and y_t^e be the returns for either the foreign exchange rates or developed stock markets, all at time *t*. CoVaR for the African stock returns for a confidence level of $(1-\beta)$ can be formally defined as the $\beta-$quantile of the conditional distribution of y_t^s as:

$$\Pr\left(y_t^s \leq CoVaR_{\beta,t}^{s|e} \mid y_t^e \leq VaR_{\alpha,t}^e\right) = \beta \qquad [5.5]$$

[67] Systemic risk may be defined as the collapse of a whole market where the failure of an idiosyncratic distress triggers a cascading failure of the entire system, as opposed to risk that is associated with only one individual entity, or group of entities, or a component of the system - Sheu and Cheng (2012). For details on systemic risk, see Sheu and Cheng (2012), Reboredo and Ugolini (2015), Pourkhanali *et al.,* (2016), Billio *et al.,* (2012), Bisias *et al.,* (2012).

where, $VaR^{e}_{\alpha,t}$ is the $\alpha-$quantile VaR of the foreign exchange rate (FER) or developed stock market (DM) distribution that quantifies the maximum loss that may be experienced by the FER or DM for a confidence level of $1-\alpha$ at time *t*.[68] Alternatively, we could estimate the systemic impact of the African stock markets on the FER and DM by computing the CoVaR for the FER and DM instead of the stock market, as in Equations [5.5] and [5.5.2]. Computing the CoVaR involves the determination of the quantile of a conditional distribution, or, better still, of an unconditional bivariate distribution upon expressing Equation [5.5] as:

$$\beta = \frac{\Pr\left[y^{s}_{t} \le CoVaR^{s|e}_{\beta,t}, y^{e}_{t} \le VaR^{e}_{\alpha,t}\right]}{\Pr\left[y^{e}_{t} \le VaR^{e}_{\alpha,t}\right]} \qquad [5.5.1]$$

Given that $\Pr\left(y^{e}_{t} \le Var^{e}_{\alpha,t}\right) = \alpha$, the CoVaR in Equation [5.5.1] can be re-written as:

$$\Pr\left(y^{s}_{t} \le CoVaR^{s|e}_{\beta,t}, y^{e}_{t} \le VaR^{e}_{\alpha,t}\right) = \alpha\beta \qquad [5.5.2]$$

We use the copulas to compute the CoVaR. To obtain the CoVaR therefore, we express Equation [5.5.2] in terms of the joint distribution function of y^{s}_{t} and y^{e}_{t}, $F_{s,e}$ as:

$$F_{s,e}\left(y^{s}_{t}, y^{e}_{t}\right) = C\left(u_{s}, u_{e}\right), \qquad [5.5.3]$$

where $C(.,.)$ is a copula function, $u_{s} = F_{s}\left(y^{s}_{t}\right)$ and $u_{e} = F_{e}\left(y^{e}_{t}\right)$, and F_{s}, F_{e} are the marginal distribution functions of y^{s}_{t} and y^{e}_{t}, respectively. Consequently, Equation [5.5.2] can be expressed in terms of copulas as:

$$C\left(F_{s}\left(CoVaR^{s|e}_{\beta,t}\right), F_{e}\left(VaR^{e}_{\alpha,t}\right)\right) = \alpha\beta \qquad [5.5.4]$$

$$1 - F_{s}\left(CoVaR^{s}_{\beta,t}\right) - F_{e}\left(VaR^{e}_{1-\alpha,t}\right) + C\left(F_{s}\left(CoVaR^{s}_{\beta,t}\right), F_{e}\left(VaR^{e}_{1-\alpha,t}\right)\right) = \alpha\beta \qquad [5.5.5]$$

We can now compute the CoVaR from Equations [5.5.4] and [5.5.5] using a two-step approach (Reboredo and Ugolini, 2015; Reboredo *et al.,* 2016).

[68] $\Pr\left(y^{e}_{t} \le Var^{e}_{\alpha,t}\right) = \alpha$

i. Given that $C(u_s, u_e) = \alpha\beta$, and $\alpha, \beta, and\, u_e$ are given and that $u_e = \alpha$ from the specification of the copula function, we can determine the value of $u_s = F_s\left(CoVaR_{\beta,t}^{s|e}\right)$.

ii. With *u* we can derive CoVaR as the quantile of the distribution of y_t^s, with a cumulative probability equal to *u*, by inverting the marginal distribution function of y_t^s: $CoVaR_{\beta,t}^{s|e} = F_s^{-1}(u_s)$.

The use of copula to estimate CoVaR has two key advantages relative to other parametric bivariate functions. First, the copulas allow much flexibility in modelling marginals as it allows separate modelling of the marginal and dependence structures. This flexibility is of great significance because marginal and dependence functions may exhibit different tail dependence features affecting the CoVaR. The copulas are also useful when the joint distribution function is not elliptical and also the traditional dependence measure given by the linear correlation coefficient is insufficient to describe the dependence structure (see Embrechts *et al.,* 2002; Reboredo and Ugolini, 2015).

The significance of the systemic spillover is tested by comparing the cumulative distribution for CoVaR $\left(CoVaR_{\beta,t}^{s}\right)$ and the VaR $\left(VaR_{\beta,t}^{s}\right)$ of *s* or *e* using the Kolmogorov-Smirnoff (KS) bootstrap technique by Abadie (2002) to comapare CoVaR values. We use the KS statistic to test the hypothesis of equality or no systemic impact between the conditional and unconditional African stock market return quantiles as:

Hypothesis: $H_0 : CoVaR_{\beta,t}^{s} = VaR_{\beta,t}^{s}$

$H_1 : CoVaR_{\beta,t}^{s} < VaR_{\beta,t}^{s}$

The K-S estimates the difference between two cumulative quantile functions relying on the empirical distribution function but without considering any underlying distribution function (Reboredo *et al.,* 2016). It is represented mathematically as:

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} \sup_x | F_m(x) - G_n(x) | \qquad [5.5.7]$$

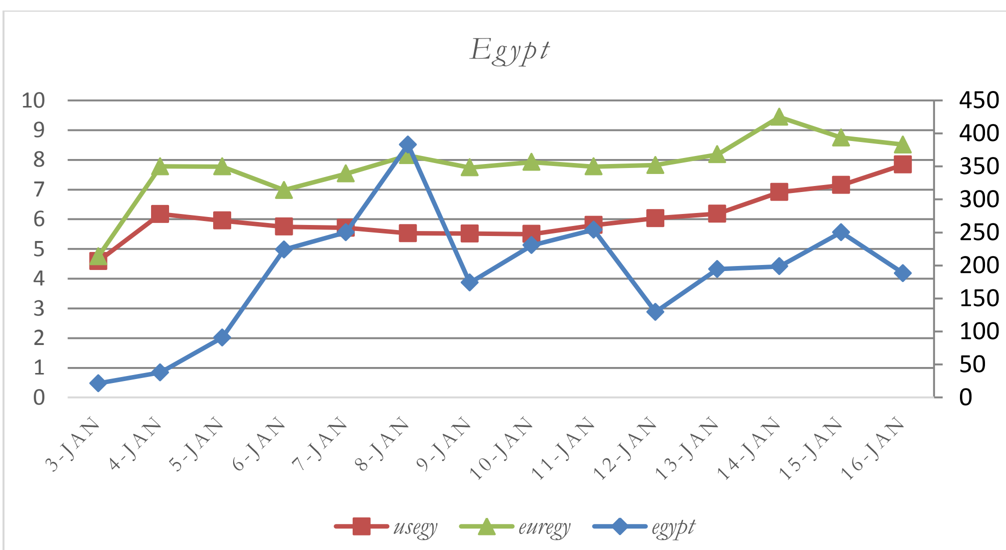
where $F_m(x)$ and $G_n(x)$ respectively, denote the cumulative conditional (CoVaR) and unconditional (VaR) quantile distribution functions for the African stock market, in that order, and *n* and *m* denote the size of the two samples.

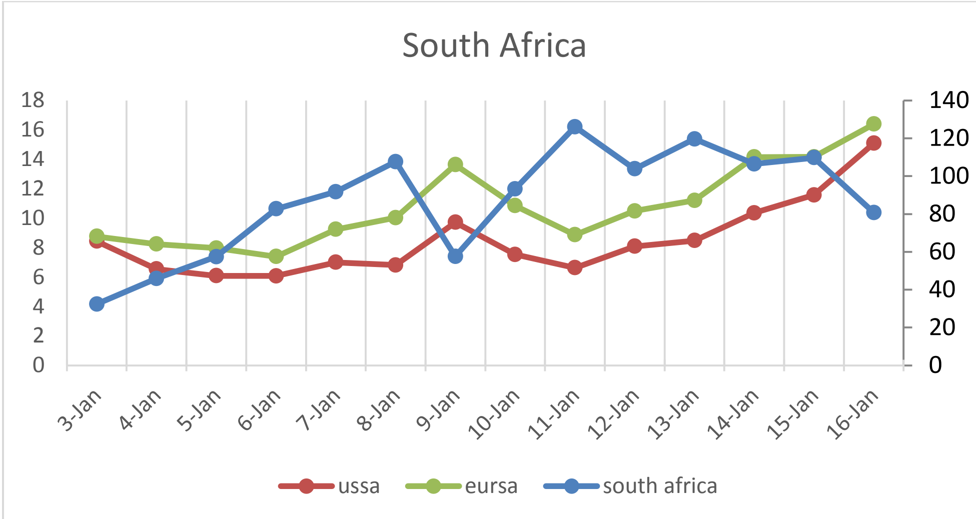
5.3 Empirical results and discussion

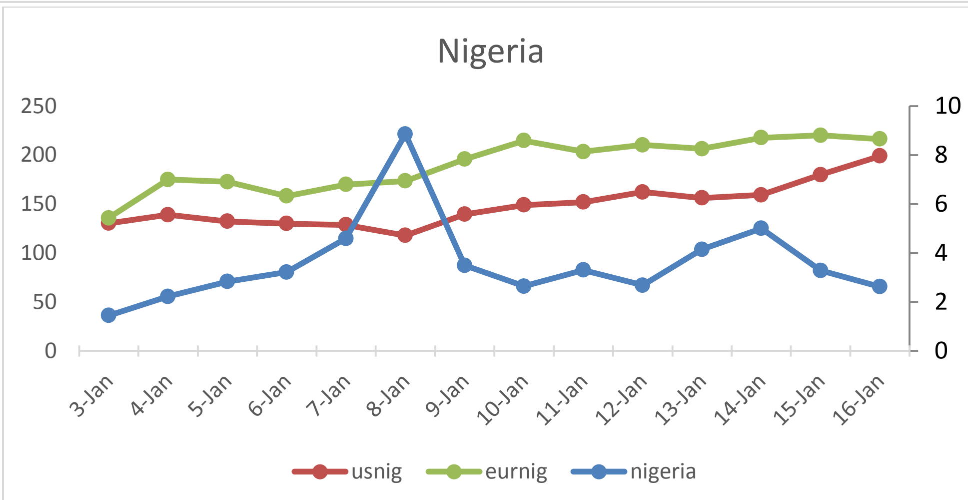
5.3.1 Baseline results

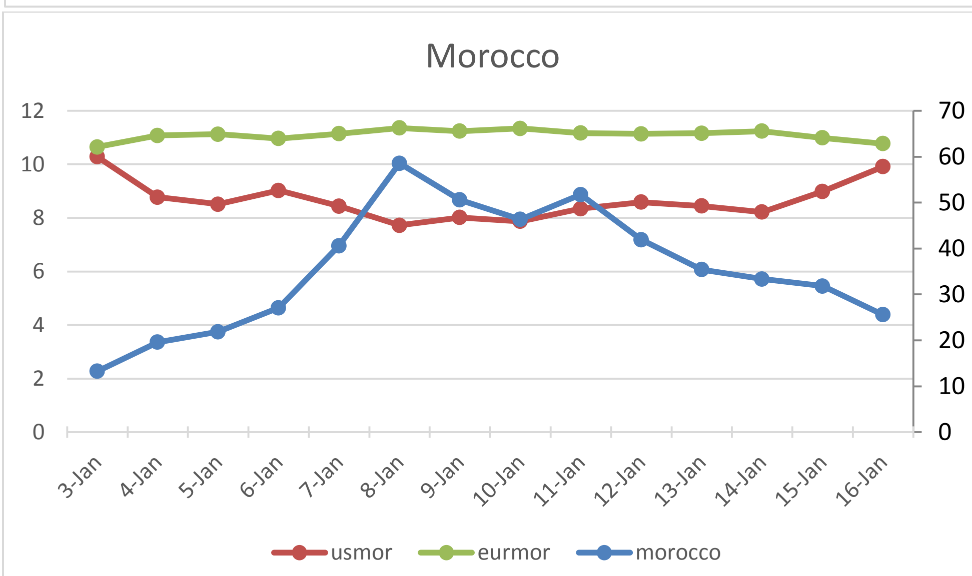
Figures 5.0*a* and *b* present preliminary analysis of temporal dynamics in the stock markets of each of the six economies in Africa, their counterpart global equity markets, and the EUR and USD exchange rates against the domestic currencies. Initial observations from Fig. *5.0a* give very little indication of domestic currency appreciation/depreciation linked with changes in stock market values. However, evidence abounds to the fact that price volatility in both the exchange rate and stock markets varied across time and countries, with the intensity of changes becoming more observable during 2008-2009 corresponding to the period of the collapse of Lehman Brothers. This may give some indication of temporal dependence between exchange rates and stock prices. The observation in Fig. *5.0b* rather shows some evidence of joint movements between the African and some developed stock markets, albeit episodic, mostly around 2008-2009.

Table 5.2 shows summary statistics of stock (local and global) and domestic exchange rates (against the EUR and USD) markets. Results in Panel A shows that returns for both local and global stock markets averaged close to zero during the sample period, with differences in standard deviations suggesting dispersion in volatility behaviour across markets. All series exhibit leptokurtic innovations with negatively skewed distributions except the market in Kenya which has positive skewness. Following the fat-tails distribution, the normality assumption is violated by the Jacque-Bera statistics. The evidence of non-normality of the series is corroborated by the normal *qq* plots in Figure 5.1.




South Africa
18
16
14
12
10
8
6
4
2
0
140
120
100
80
60
40
20
0
3-Jan
4-Jan
5-Jan
6-Jan
7-Jan
8-Jan
9-Jan
10-Jan
11-Jan
12-Jan
13-Jan
14-Jan
15-Jan
16-Jan
ussa
eursa
south africa


Nigeria
250
200
150
100
50
0
10
8
6
4
2
0
3-Jan
4-Jan
5-Jan
6-Jan
7-Jan
8-Jan
9-Jan
10-Jan
11-Jan
12-Jan
13-Jan
14-Jan
15-Jan
16-Jan
usnig
eurnig
nigeria


Morocco
12
10
8
6
4
2
0
70
60
50
40
30
20
10
0
3-Jan
4-Jan
5-Jan
6-Jan
7-Jan
8-Jan
9-Jan
10-Jan
11-Jan
12-Jan
13-Jan
14-Jan
15-Jan
16-Jan
usmor
eurmor
morocco

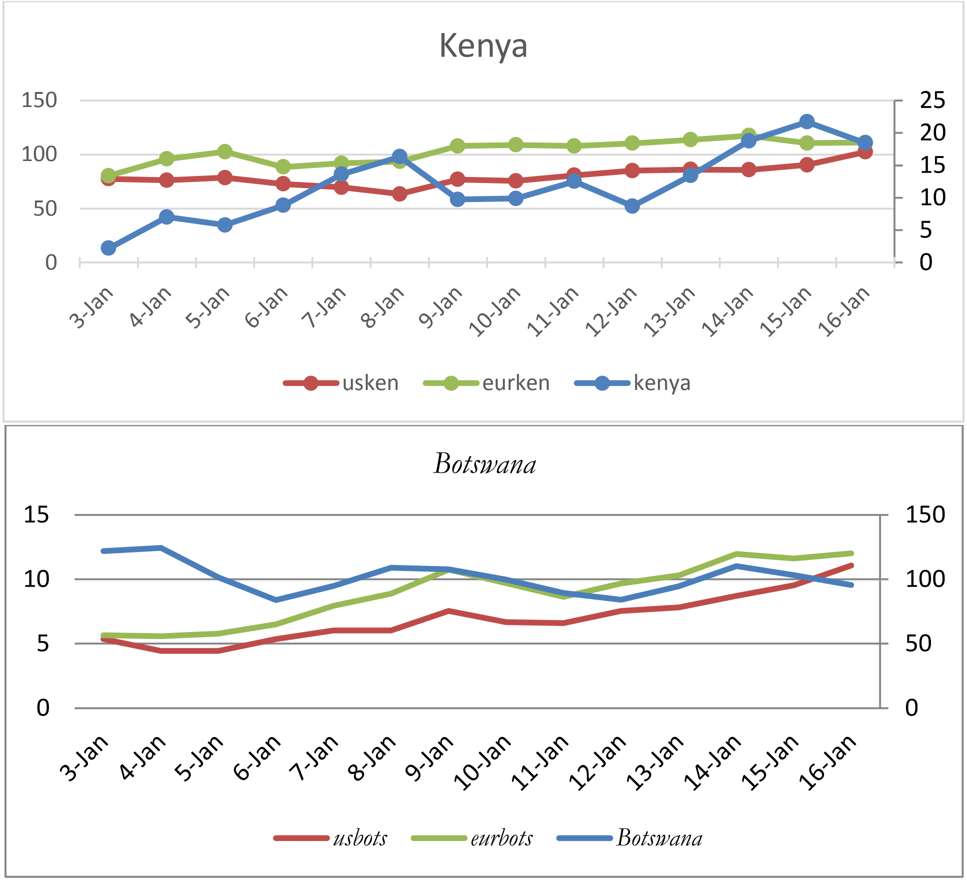
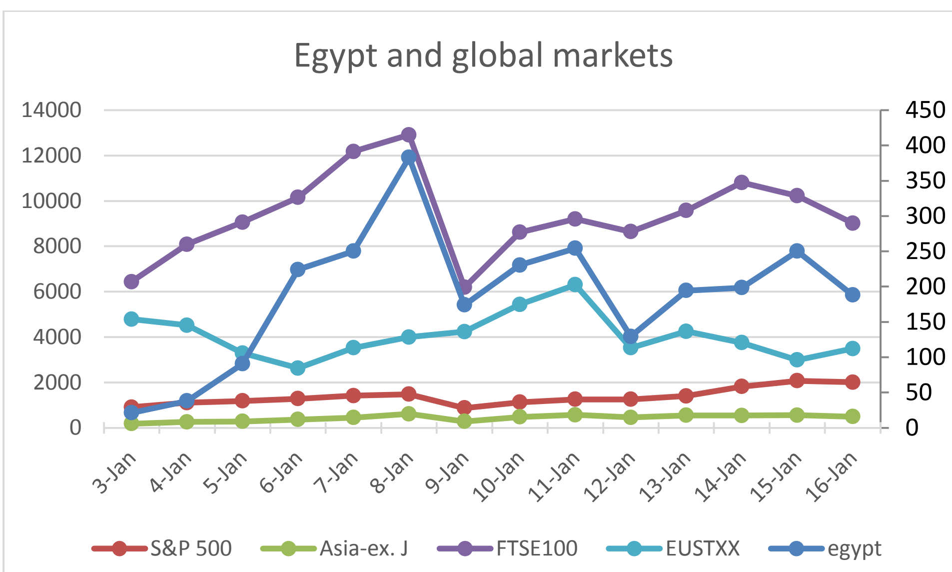
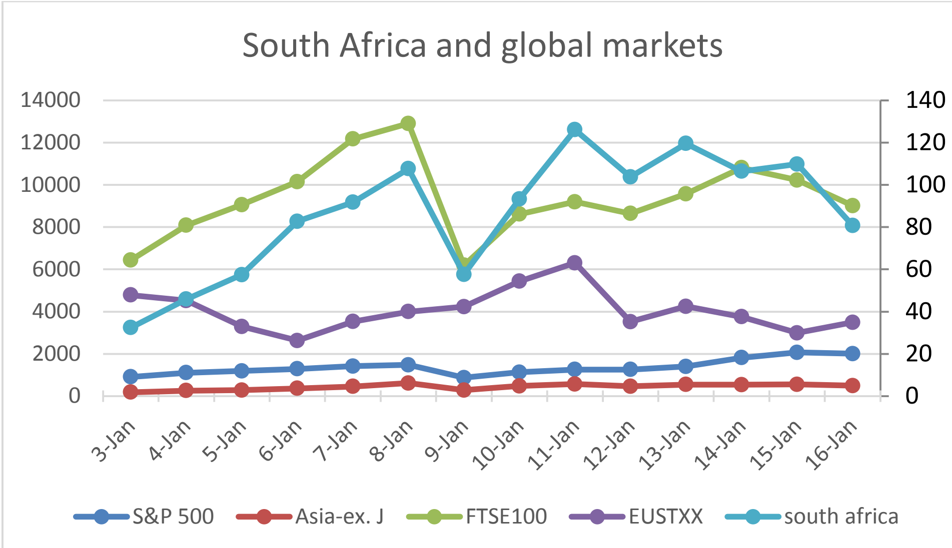
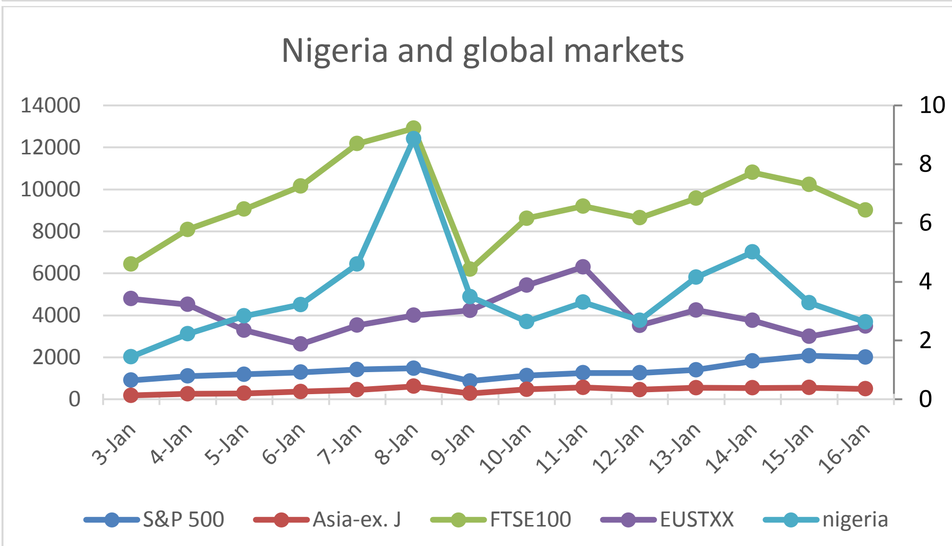
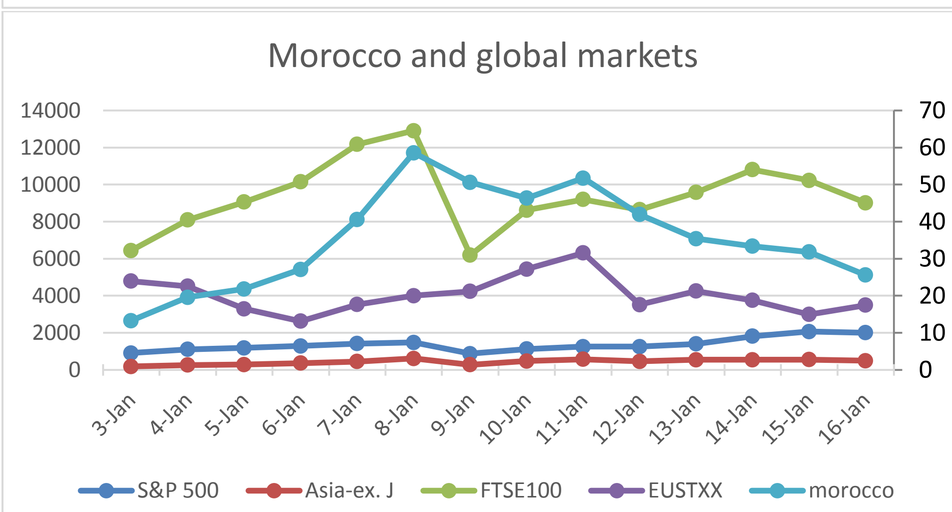


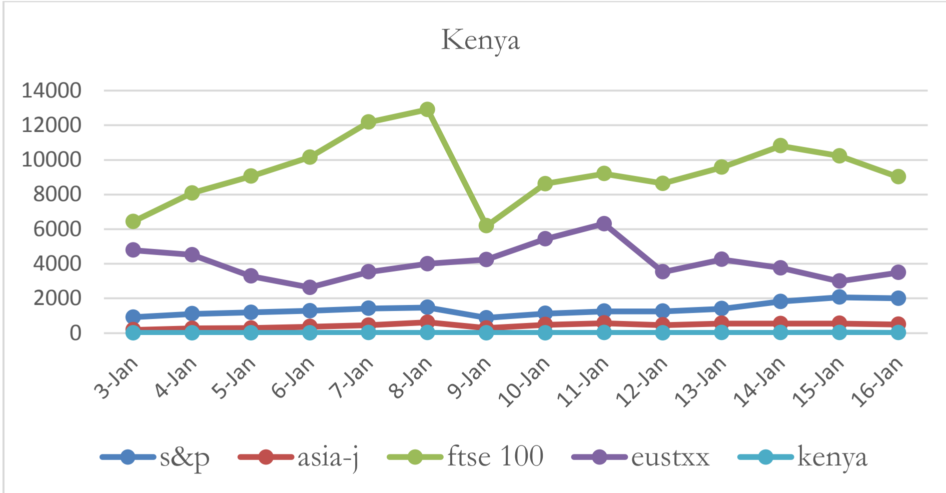
Figure 5.0a: Time series plots of weekly stock market indices and EUR and USD exchange rates in Africa from January 2003 to February 2016.




South Africa and global markets
14000
12000
10000
8000
6000
4000
2000
0
140
120
100
80
60
40
20
0
3-Jan 4-Jan 5-Jan 6-Jan 7-Jan 8-Jan 9-Jan 10-Jan 11-Jan 12-Jan 13-Jan 14-Jan 15-Jan 16-Jan
S&P 500
Asia-ex. J
FTSE100
EUSTXX
south africa


Nigeria and global markets
14000
12000
10000
8000
6000
4000
2000
0
10
8
6
4
2
0
3-Jan 4-Jan 5-Jan 6-Jan 7-Jan 8-Jan 9-Jan 10-Jan 11-Jan 12-Jan 13-Jan 14-Jan 15-Jan 16-Jan
S&P 500
Asia-ex. J
FTSE100
EUSTXX
nigeria


Morocco and global markets
14000
12000
10000
8000
6000
4000
2000
0
70
60
50
40
30
20
10
0
3-Jan 4-Jan 5-Jan 6-Jan 7-Jan 8-Jan 9-Jan 10-Jan 11-Jan 12-Jan 13-Jan 14-Jan 15-Jan 16-Jan
S&P 500
Asia-ex. J
FTSE100
EUSTXX
morocco



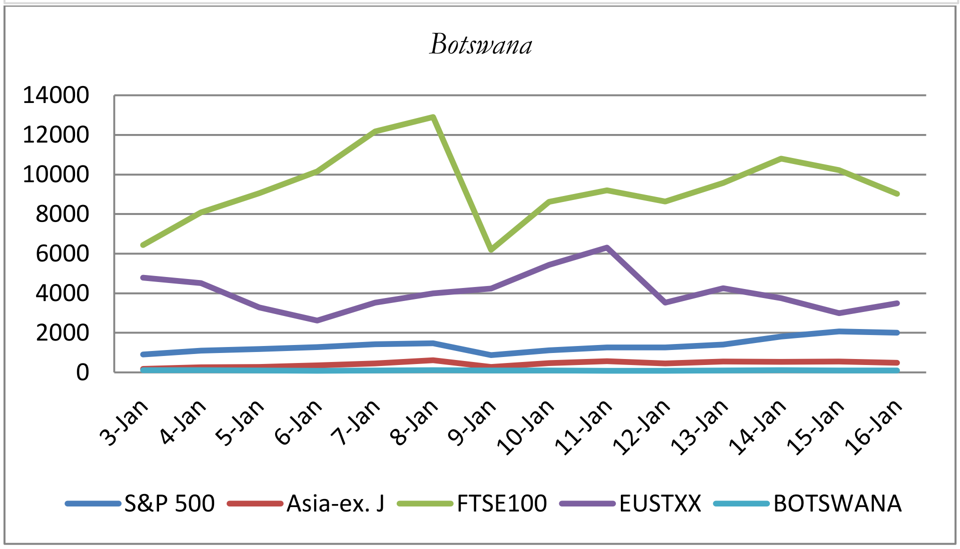


Figure 5.0b: Time series plots of weekly stock market indices (Africa and developed) from January 2003 to February 2016.

Intuitively, the strong departure from linearity at the end of the *qq* plots suggests non-normal fat-tailed behaviour of all the series, consistent with the kurtosis values. The stark evidence against normality of the series makes the use of conditional correlations and multivariate normal distributions inappropriate in examining the data. Both the Ljung-Box and Breusch-Godfrey Lagrange multiplier (LM) statistics at 20 lags indicate the existence of serial correlation in most of the markets. Panels B and C of Table 5.2, respectively depicts the summary measures for the USD and EUR against the domestic currencies. Similar to results in Panel A, returns and standard deviations averaged close to zero. Skewness was mainly positive for the EUR (except Kenya and Morocco) and USD (except Kenya). Both exchange rates display fat-tails, with consequential non-normality of returns distributions. Additionally, evidence of serial correlation is found for most of the exchange rate pairs as reported by the Ljung-Box and Breusch-Godfrey Lagrange multiplier (LM) statistics at 20 lags.

5.3.2 Marginal model results

Tables 5.3-5 present results obtained from the estimation of marginal models in Equations (5.2) and (5.2.1) for the stock markets (domestic and developed) and the EUR and USD exchange rates against the domestic currency. The model parameters were chosen for a range of values of p, q, v, and s from zero to two in order to minimize the AIC values. Tables 5.3 and 5.4, respectively show the marginal model results for the EUR and USD exchange rates with domestic currencies. The empirical evidence suggest that average returns of the EUR and USD exchange rates report generally 'near-no' serial correlation, with commonly highly persistent volatilities (as shown by the volatility estimates – ARCH and GARCH) across countries for the two foreign exchange rates. We find no evidence of leverage effects for the EUR exchange rates except with the Botswana Pula and South African Rand. For the USD exchange rate pair, evidence of leverage effects abounds with all local currencies except the Kenya Shillings. Evidence of leverage effects suggests that currency markets' (especially with the USD) responses to informational shocks during the sample period was asymmetrical. The goodness of fit results submit that serial correlation and 'ARCH effects' were generally absent for the two foreign exchange rates.

Table 5.5 shows marginal model parameter estimates for the stock markets. Results indicate that there was no 'ARCH effects' in average returns of all series. Whereas, the Ljung-Box test results for the squared residual model report no evidence of serial correlation, we find evidence of temporal serial dependences in the residual model for the Botswana, Egypt, and FTSE100 stock markets. Additionally, leverage effects were present for more than two-thirds of the markets, positing that the stock markets responded symmetrical to informational shocks during the sample period. The highly significant GARCH parameters give indication of highly persistent volatility in the returns of the series.

5.3.3 Empirical evidence on dependence using Copulas

This section examines the results for copula estimates in both the static and time-varying framework for each pair of an African stock market against each of the two foreign exchange rates (EUR and USD) and the four developed stock markets (Asia ex-J, FTSE100, EUSTX, and S&P500). For

Table 5.2: Summary statistics

	Botswana	Egypt	Kenya	Morocco	Nigeria	South Africa	Asia ex-Japan	EUSTXX	FTSE100	S&P 500
Panel A: Stock markets indices										
Mean	-0.001	0.003	0.003	0.001	0.001	0.001	0.001	0.002	0.001	0.001
Std. Dev	0.047	0.043	0.039	0.026	0.044	0.041	0.029	0.035	0.030	0.024
Skewness	-14.709	-0.871	0.157	-0.486	-0.285	-0.041	-0.727	-1.121	-1.390	-0.923
Kurtosis	318.490	6.626	7.919	5.811	6.170	8.555	7.519	10.406	16.528	12.145
J-B	2861388*	461.109*	692.339*	252.057*	295.677*	879.537*	642.056*	1706.458*	5435.601*	2480.793*
Q(20)	26.574	43.806	22.899	31.678	34.757	35.203	33.861	47.307	61.685	39.493
	[0.148]	[0.002]	[0.294]	[0.047]	[0.021]	[0.019]	[0.027]	[0.001]	[0.000]	[0.006]
B-G	1.205	1.943	1.049	1.462	1.507	1.762	1.654	2.527	3.296	2.083
	[0.242]	[0.008]	[0.401]	[0.088]	[0.072]	[0.021]	[0.036]	[0.000]	[0.000]	[0.004]
Panel B: USD exchange rate against the domestic currency										
Mean	0.001	0.001	0.000	-2.12E-05	0.001	0.001				
Std. Dev	0.019	0.007	0.010	0.011	0.010	0.024				
Skewness	1.329	13.465	-0.358	0.313	1.811	0.369				
Kurtosis	13.034	272.492	9.625	4.133	15.883	5.763				
J-B	3070.394*	209050*	1265.505*	47.704*	5103.735*	233.127*				
Q(20)	26.088	57.233	41.152	16.818	47.272	32.378				
	[0.163]	[0.000]	[0.004]	[0.665]	[0.001]	[0.039]				
B-G	1.292	2.356	2.000	0.907	2.440	1.573				
	[0.176]	[0.001]	[0.006]	[0.578]	[0.001]	[0.053]				
Panel C: EUR exchange rate against the domestic currency										
Mean	0.001	0.001	0.000	1.36E-05	0.002	0.001				
Std. Dev	0.016	0.015	0.016	0.003	0.017	0.022				
Skewness	0.983	0.928	-0.513	-0.298	0.458	0.248				
Kurtosis	8.826	14.314	5.560	4.615	6.420	6.084				
J-B	1077.316*	3746.548*	216.811*	84.511*	357.222*	278.179*				
Q(20)	34.526	32.646	18.911	22.326	25.040	39.070				
	[0.023]	[0.037]	[0.528]	[0.323]	[0.200]	[0.007]				
B-G	1.642	1.617	0.931	1.204	1.357	1.727				
	[0.038]	[0.043]	[0.548]	[0.244]	[0.136]	[0.025]				

Notes: Data are weekly running from January 2003 to February 2016. '' denote statistical significance at 1%, J-B is the Jacque-Bera statistics for estimating normality, Std. Dev is standard deviation, Q(20) is the Ljung-Box statistics and B-G denotes the Breusch-Godfrey LM statistics. Both the Q(20) and B-G are used to test serial correlation in returns at 20 lags. The p-values for these tests are reported in squared brackets.*

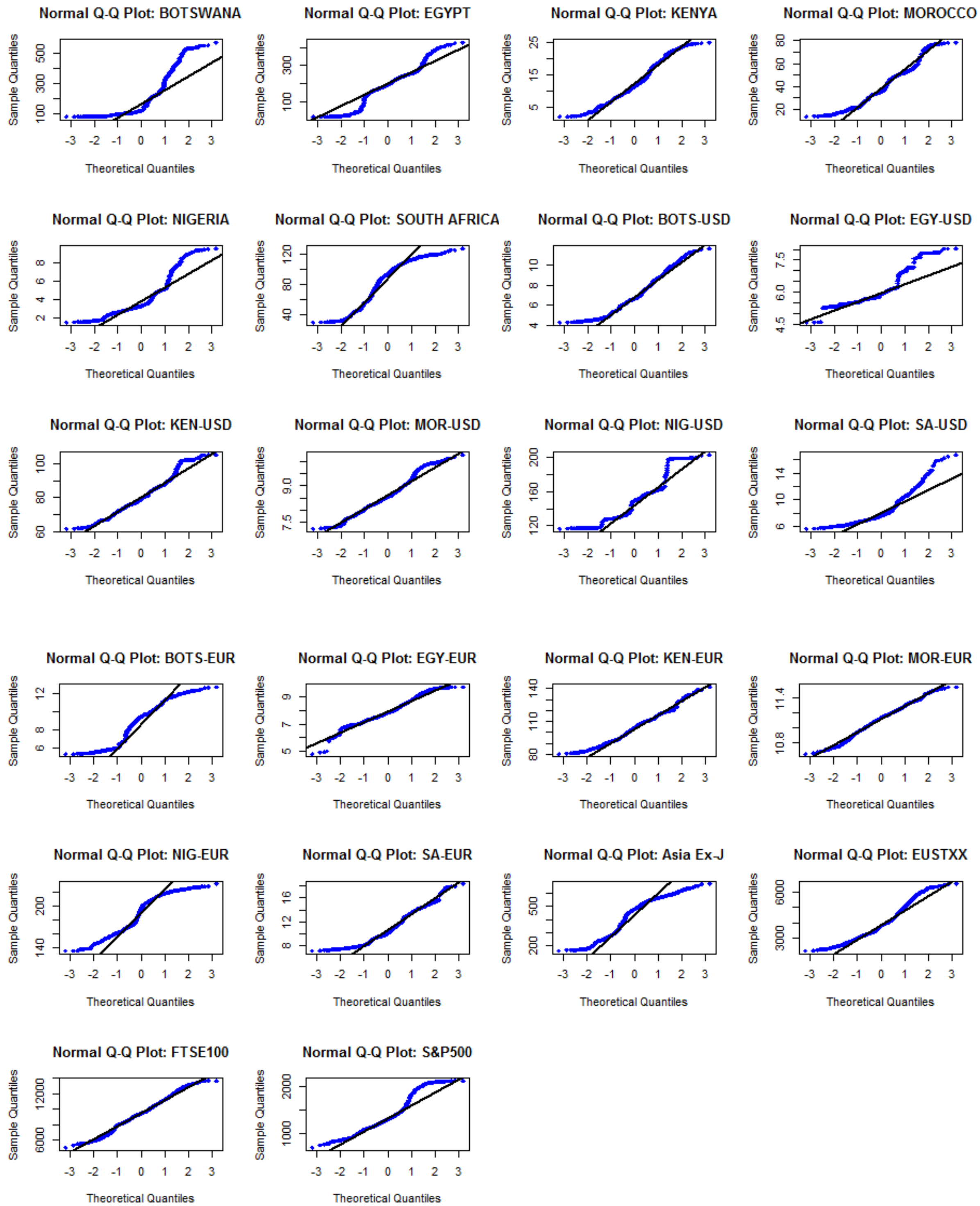


Figure 5.1: Normal *qq* plots of all returns

Table 5.3: Parameter estimates for marginal models of domestic currency against EUR exchange rate

	Botswana	Egypt	Kenya	Morocco	Nigeria	South Africa
Mean						
φ	0.00	0.00	-4.06E-05	-3.93E-05	0.00	0.00*
	[1.51]	[0.26]	[-0.08]	[-0.39]	[0.20]	[4.59]
θ_1	-0.15*	-0.99*		0.26*	1.25*	0.25*
	[-3.39]	[-352.99]		[26.24]	[108.93]	[4.57]
θ_2				-0.97*	-0.96*	0.71*
				[-111.67]	[-84.08]	[13.12]
ϕ_1		0.99*		-0.29*	-1.29*	-0.33*
		[1187.17]		[-72.88]	[-243.24]	[-6.55]
ϕ_2				0.99*	0.99*	-0.66*
				[234.31]	[204.22]	[-12.92]
Variance						
ϖ	5.56E-05*	1.04E-05*	3.42E-06	9.42E-08	9.84E-06**	0.00*
	[6.71]	[2.97]	[1.56]	[1.28]	[2.37]	[4.06]
α	0.33*	0.11*	0.09*	0.10*	0.15*	0.23*
	[6.57]	[3.31]	[3.34]	[2.93]	[4.69]	[4.29]
β	0.60*	0.83*	0.89*	0.89*	0.83*	0.58*
	[14.61]	[25.53]	[41.32]	[37.94]	[25.74]	[6.30]
λ	-0.26*	0.02	0.03	0.01	-0.00	-0.22*
	[-4.88]	[0.54]	[0.90]	[0.25]	[-0.01]	[-3.73]
LogLik	1880.16	1945.55	1906.47	3029.77	1867.85	1661.56
LJ1	21.32	24.02	17.36	13.41	13.74	28.61
	(0.32)	(0.15)	(0.63)	(0.64)	(0.62)	(0.03)
LJ2	5.65	11.07	29.84	20.67	15.50	17.24
	(0.10)	(0.94)	(0.07)	(0.42)	(0.75)	(0.64)
ARCH-LM	0.26	0.57	1.61	1.04	0.70	0.89
	(0.99)	(0.93)	(0.05)	(0.41)	(0.82)	(0.60)

Notes: The table shows parameter estimates with z statistics (in square brackets) for the marginal models outlined in Eqns. (5.2) – (5.2.1). ',**,***' denotes statistical significance at the 1%, 5%, and 10% levels, respectively. LogLik represents the log-likelihood value; LJ1 and LJ2 respectively represent the Ljung-Box statistics (computed with 20 lags) for serial correlation in the residual model and squared residual model. ARCH-LM is Engle's LM test for 'ARCH effects' in residuals up to the 20th order. For LJ1, LJ2, and ARCH-LM tests, p-values (in parenthesis) less than 0.05 suggest rejection of the null hypothesis.*

Table 5.4: Parameter estimates for marginal models of domestic currency against USD exchange rate

	Botswana	Egypt	Kenya	Morocco	Nigeria	South Africa
Mean						
φ	0.00	0.00	0.00***	8.28E-05	3.23E-05	9.46E-06***
	[1.41]	[1.50]	[1.78]	[0.21]	[0.24]	[1.95]
θ_1	0.42	0.20***	1.03**	0.29*	-0.29*	-0.76*
	[1.30]	[1.70]	[2.03]	[25.65]	[-7.23]	[-2.87]
θ_2	0.04	-0.06	-0.23	-0.97*	0.06	
	[0.57]	[-1.31]	[-0.31]	[-88.40]	[1.42]	
ϕ_1	-0.55***	-0.10	-1.03**	-0.32*		-0.28
	[-1.68]	[-0.73]	[-2.05]	[-57.85]		[-0.99]
ϕ_2		0.02	0.29	0.99*		-0.72**
		[0.30]	[0.73]	[234.72]		[-2.54]
Variance						
ϖ	5.45E-05*	4.20E-06*	4.81E-06*	2.84E-06***	2.09E-06*	2.07E-05***
	[4.65]	[7.25]	[8.14]	[1.70]	[10.72]	[1.95]
α	0.38*	0.53*	0.44*	0.10*	1.24*	0.11*
	[7.72]	[4.00]	[7.17]	[3.77]	[13.84]	[4.59]
β	0.62*	0.49*	0.60*	0.91*	0.59*	0.89*
	[14.39]	[7.41]	[25.03]	[33.94]	[34.92]	[25.61]
λ	-0.25*	-0.39*	-0.02	-0.05***	-1.02*	-0.06**
	[-5.16]	[-3.03]	[-0.31]	[-1.90]	[-10.47]	[-2.24]
LogLik	1794.21	2842.44	2334.80	2127.67	2440.75	1616.41
LJ1	14.83	40.69	23.80	16.45	33.61	24.61
	(0.61)	(0.00)	(0.09)	(0.42)	(0.01)	(0.10)
LJ2	8.50	1.44	21.50	18.76	5.58	13.24
	(0.99)	(1.00)	(0.37)	(0.54)	(0.99)	(0.87)
ARCH-LM	0.39	0.07	1.12	0.84	1.23	0.61
	(0.99)	(1.00)	(0.32)	(0.67)	(0.22)	(0.91)

Notes: see notes for Table 5.3.

Table 5.5: Parameter estimates for marginal models of stock markets (domestic and developed)

	Morocco	Asia-ex. J	Botswana	Egypt	Kenya	Nigeria	South Africa	S&P 500	EUSTXX	FTSE 100
Mean										
φ	1.4E-05**	0.00**	0.00	0.00	0.00	0.00	0.00	0.00**	0.00	0.00
	[-1.97]	[2.39]	[1.54]	[1.24]	[1.33]	[1.39]	[0.44]	[2.06]	[0.42]	[0.81]
θ_1		0.03	0.45***	0.41	0.03	-0.18	0.85**	-0.79**	0.55	-0.55
		[0.65]	[1.73]	[1.56]	[0.77]	[0.46]	[2.33]	[-2.31]	[1.47]	[-0.59]
θ_2		0.07			0.88*	0.72*		0.17		0.40
		[1.63]			[25.24]	[3.14]		[0.52]		[0.43]
ϕ_1	-0.10*		-0.54**	-0.28	-0.00	0.21	-0.84**	0.72**	-0.53	0.56
	[-953.59]		[-2.24]	[-1.01]	[-0.02]	[0.43]	[-2.24]	[2.11]	[-1.41]	[0.59]
ϕ_2					-0.88*	-0.65*		-0.24		-0.39
					[-22.61]	[-2.62]		[-0.74]		[-0.43]
Variance										
ϖ	4.26E-05*	3.73E-05*	0.00*	0.00*	0.00*	0.00*	0.00*	3.36E-05*	7.62E-05*	6.45E-05*
	[2.90]	[2.86]	[5.75]	[4.37]	[4.57]	[4.30]	[3.63]	[4.56]	[3.63]	[4.41]
α	0.09*	0.03	0.04***	0.06***	0.22*	0.15*	-0.03	-0.02	-0.01	-0.02
	[2.96]	[0.82]	[1.84]	[1.93]	[4.62]	[4.49]	[-0.86]	[-0.72]	[-0.35]	[-0.72]
β	0.82*	0.83*	0.67*	0.74*	0.61*	0.78*	0.78*	O.79*	0.79*	0.77*
	[19.58]	[21.40]	[21.56]	[19.01]	[10.86]	[27.62]	[16.70]	[22.43]	[18.89]	[19.57]
λ	0.04	0.16*	0.97*	0.13*	0.07	0.03	0.26*	0.30*	0.28*	0.32*
	[1.32]	[3.08]	[5.90]	[3.62]	[1.19]	[0.90]	[5.05]	[7.02]	[7.84]	[7.12]
LogLik	1577.10	1537.77	1327.22	1213.73	1332.50	1262.93	1307.02	1715.42	1429.73	1558.68
LJ1	19.15	25.12	50.69	29.42	15.53	20.50	19.50	14.59	20.78	24.96
	(0.45)	(0.12)	(0.00)	(0.04)	(0.49)	(0.20)	(0.36)	(0.56)	(0.29)	(0.07)
LJ2	24.63	13.84	1.33	22.01	16.80	19.81	13.73	19.63	14.87	22.97
	(0.22)	(0.84)	(1.00)	(0.34)	(0.67)	(0.47)	(0.84)	(0.48)	(0.78)	(0.29)
ARCH-LM	1.23	0.73	0.06	1.22	0.88	0.95	0.67	1.07	0.72	1.10
	(0.22)	(0.80)	(1.00)	(0.23)	(0.61)	(0.52)	(0.86)	(0.38)	(0.81)	(0.34)

Notes: see notes for Table 5.3.

instance, Kenya with the rest of the combination, and so on. The static copulas are defined by the following distributions – *Gaussian, Student-t, Gumbel, and rotated Gumbel* in Panel A of each table. Their time-varying counterparts are prefixed with the abbreviation (TVP) in all Panel Bs. Sub-section 5.3.3.1 discusses the copula model estimates between African stocks and foreign exchange rates (with Tables 5.6 and 5.7, and Figure 5.2a&b) and sub-section 5.3.3.2 does same for African and developed stock markets (with Tables 5.8-5.11 and Figures 5.3a-d). In all, best fitting copulas are selected based on AICs. Estimates are based on observations of the probability integral transformation of the standardized residuals from the marginal models reported in the tables.

5.3.3.1 African stock and exchange rate markets

This section examines the results for copula estimates in both the static and time-varying framework for each of the African stock market against each of the two foreign exchange rates (EUR and USD). Observation of the results shows some desirable features notable for discussion. First, in Table 5.6, we find that each stock market returns in a way exhibit negative constant dependence with the returns of the USD exchange rate, except that of Egypt. Except for South Africa which showed dependence estimate of -0.74, the Gaussian copula parameter (a measure of constant conditional correlation in the static framework) estimates for all market pairs were less than 0.5. The lowest correlation pair was Egypt-USD with a value of 0.049. The evidence of negative dependence between stocks and the USD exchange rate implies that higher (lower) equity prices are accompanied with depreciation (appreciation) of domestic currencies, expressed in USD terms.

As we compare the different copula specifications, it is observed that the AIC selects different copulas as best fit for different pairs. The best fit copulas are indicated in bold. In terms of time-varying tail measures, we notice that time-varying lower tail dependence (as shown by the TVP-rotated Gumbel copula) is observed for the South African stock returns and the returns of the USD exchange rate. Time- varying average dependence, as given by the Student-t copula was found for each of Nigeria and Botswana, on one hand and the USD exchange rate returns, on the other hand. This implies that in South Africa, stock returns are in a way coupled on average and in bearish markets, but decoupled in bullish markets with the USD exchange rate. The result is similar to that of Boako *et al.,* (2016) who find inverse dependence between returns of the Ghana equity market and the USD exchange rate with the local currency using the Bayesian quantile regression technique,

Table 5.6: Bivariate copula model estimates for African stock market and USD exchange rate returns

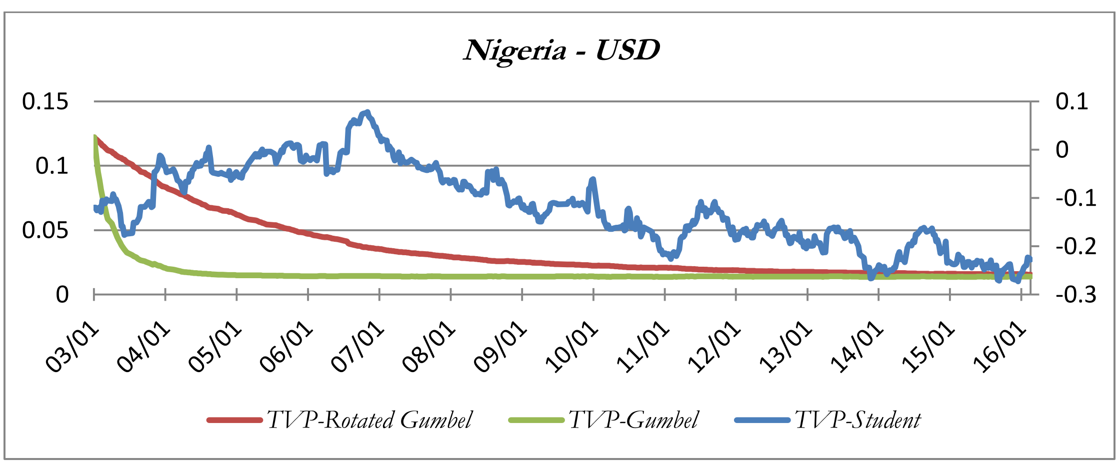
	Kenya	South Africa	Egypt	Nigeria	Morocco	Botswana
Panel A: Time-invariant copulas						
Gaussian						
ρ	-0.422*	-0.744*	-0.049	0.114*	-0.461*	-0.290*
	[0.029]	[0.014]	[0.040]	[0.042]	[0.028]	[0.029]
AIC	**-164.075**	-539.4	0.383	-3.086	-157.000	-56.30
Student-t copula						
ρ	-0.425*	-0.753*	-0.047	0.101*	-0.460*	-0.313*
	[0.034]	[0.016]	[0.045]	[0.037]	[0.033]	[0.035]
ν	5.989*	6.447*	199.265*	59.308*	10.470	12.270*
	[1.784]	[0.016]	[3.926]	[1.303]	[2.186]	[2.001]
AIC	-141.317	-560.218	0.621	-8.025	**-161.804**	-60.125
Gumbel						
δ	1.000*	1.000*	1.000*	1.000*	1.000*	1.000*
95% CI	(0.955-1.045)	(0.959-1.041)	(0.951-1.049)	(0.969-1.031)	(0.955-1.045)	(0.961-1.039)
AIC	82.266	130.287	34.469	39.007	87.278	66.657
Rotated Gumbel						
δ	1.000*	1.000*	1.000*	1.000*	1.000*	1.000*
95% CI	(0.956-1.044)	(0.959-1.041)	(0.966-1.034)	(0.962-1.039)	(0.955-1.045)	(0.967-1.033)
AIC	81.691	129.13	26.491	40.215	92.057	66.240
Panel B: Time-varying copulas						
TVP-Gaussian						
ψ_1	0.120*	0.066*	1.77E-05	0.011*	0.022	0.023*
	[0.035]	[0.032]	[0.009]	[0.006]	[0.050]	[0.004]
ψ_2	0.681*	0.912*	0.982*	0.981*	0.606	0.977
	[0.097]	[0.057]	[0.156]	[0.006]	[2.580]	[0.000]
AIC	-149.502	-611.505	**-12.613**	-10.318	-155.734	-91.248
TVP-Student						
ψ_0	5.811*	9.916*	199.878*	73.755*	10.711*	13.596*
	[1.590]	[3.854]	[0.019]	[1.059]	[4.92]	[5.916]
ψ_1	0.131*	0.077*	0.000	0.011*	0.021	0.022*
	[0.035]	[0.026]	[0.003]	[0.006	[0.038]	[0.005]
ψ_2	0.712*	0.903*	0.985*	0.981*	0.681	0.978
	[0.085]	[0.041]	[0.368]	[0.008]	[1.179]	[0.000]
AIC	-128.204	31.159	4.621	**-18.441**	-158.542	**-92.006**
TVP-Gumbel						
ω	-0.021	-0.021	-0.016	-0.192*	-0.021	-0.022
	[0.017]	[0.036]	[0.235]	[0.052]	[0.105]	[0.000]
α	-0.001	0.005	0.030	0.004	-0.002	-0.005
	[0.017]	[0.018]	[0.021]	[0.036]	[0.050]	[0.011]
β	0.996*	0.995*	0.996*	0.958*	0.996*	0.996*
	[0.008]	[0.009]	[0.012]	[0.011]	[0.026]	[0.103]
AIC	26.644	31.314	12.045	8.941	27.967	15.627
TVP-Rotated Gumbel						
ω	-0.021	-0.251*	-0.021	-0.021	-0.021	-0.013
	[0.124]	[0.134]	[0.000]	[0.035]	[0.063]	[1.045]
α	-0.005	-0.076	0.010	-0.004	-0.005	0.025
	[0.010]	[0.065]	[0.014]	[0.017]	[1.060]	[0.034]
β	0.996*	0.949*	0.995*	0.996*	0.996*	0.996*
	[0.120]	[0.056]	[0.001]	[0.002]	[0.045]	[0.107]
AIC	28.686	**-617.348**	9.141	10.920	31.489	19.271

Notes: The table shows results of static/time-invariant and time-varying bivariate copula models for African stock markets and USD exchange rate returns. Standard errors and confidence intervals are shown in square brackets [] and parenthesis (), respectively. Alkaike information criterion (AIC) values adjusted for small-sample bias are reported for the different copula models; the minimum AIC value [in bold] indicates the best copula fit; '' denotes statistical significance of the parameter at 5%. CI is confidence interval.*

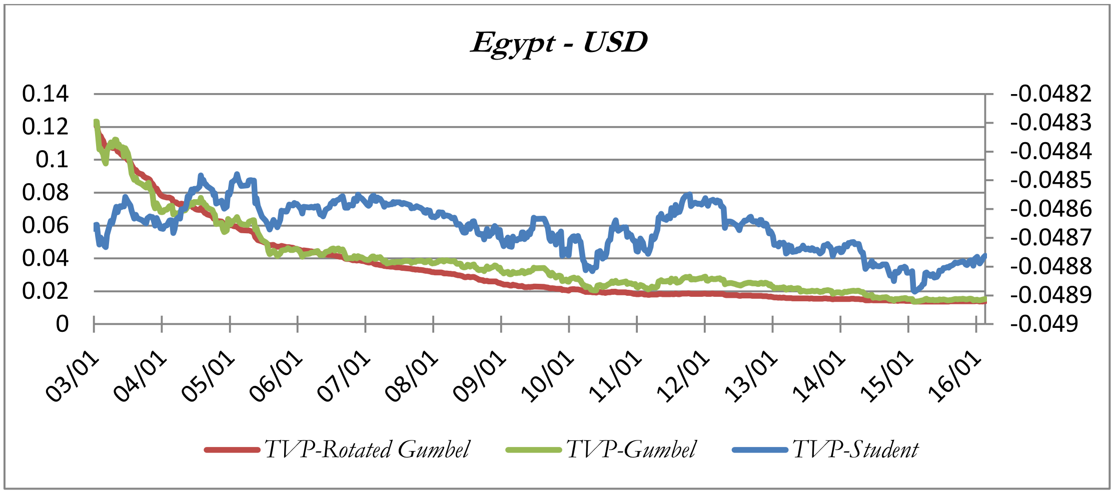
and infers that such occurrences suggest dollar denominated assets can offer better diversification opportunity to investors during turbulent periods of the equity market. Another observation is that investors usually develop reduced appetite for portfolio investments during market upturns leading to reduced foreign capital flows (that is flight-to-quality), with the attendant debilitating effects on the performance of the local currency – see also, Reboredo *et al.,* (2016) and Cho *et al.,* (2016). This may occur through the portfolio balance theory. Considering that South Africa remains the highest recipient of foreign portfolio capital flows on the continent, any negative changes in the flow of foreign portfolio capital would invariably affect the performance of the local currency. Thus, the government of South Africa could therefore stimulate the performance of the local currency (Rand) by ensuring higher economic growth through the local bourse.

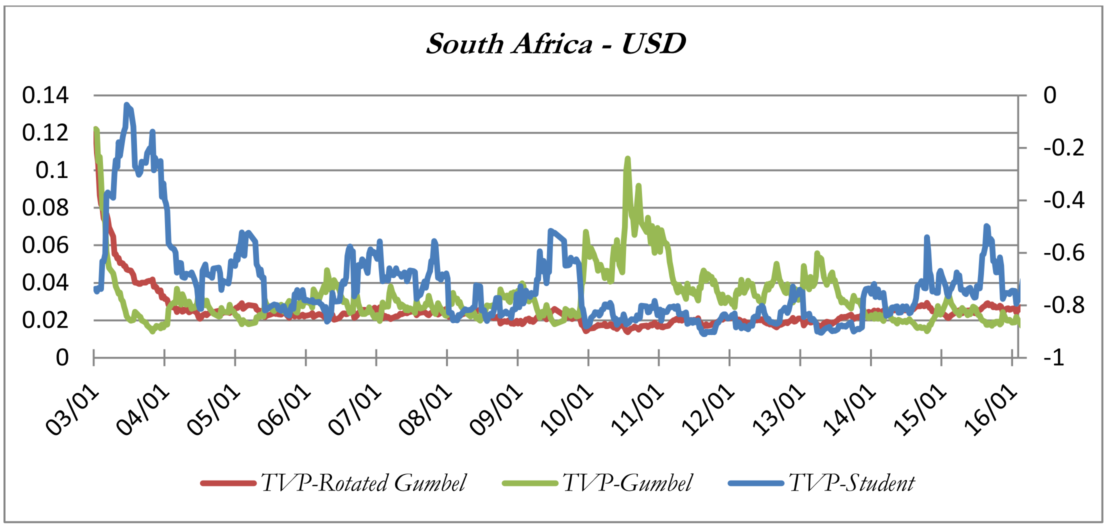
In contrast, the Nigerian and Botswana stock market returns show dependence with the local exchange rate returns, expressed in USD terms, irrespective of the market condition. This maybe so perhaps, partly because the main driving force in the Nigerian and Botswana currency is oil and Diamond price changes, respectively and not the equity markets. More so, the size of the stock market relative to the entire economy is far small in Nigeria and Botswana compared to South Africa. Listed domestic companies market capitalization as a percentage of GDP from 2011 to 2014 was 9.5, 12.2, 15.7, and 11.2, respectively for Nigeria. Correspondingly, that for South Africa for the same period was 189.4, 228.4, 257.4, and 266.7, respectively. For Botswana, the percentage figures are 25.1 (2011), 23.8 (2012), and 34.3 (2015).[69]

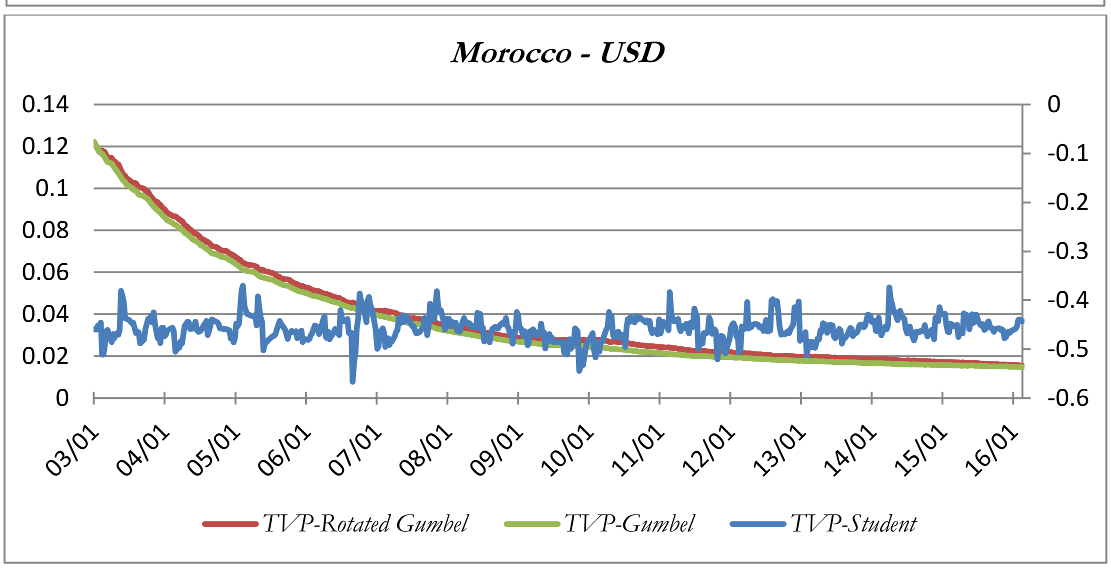
Panel A: African stock market and USD exchange returns

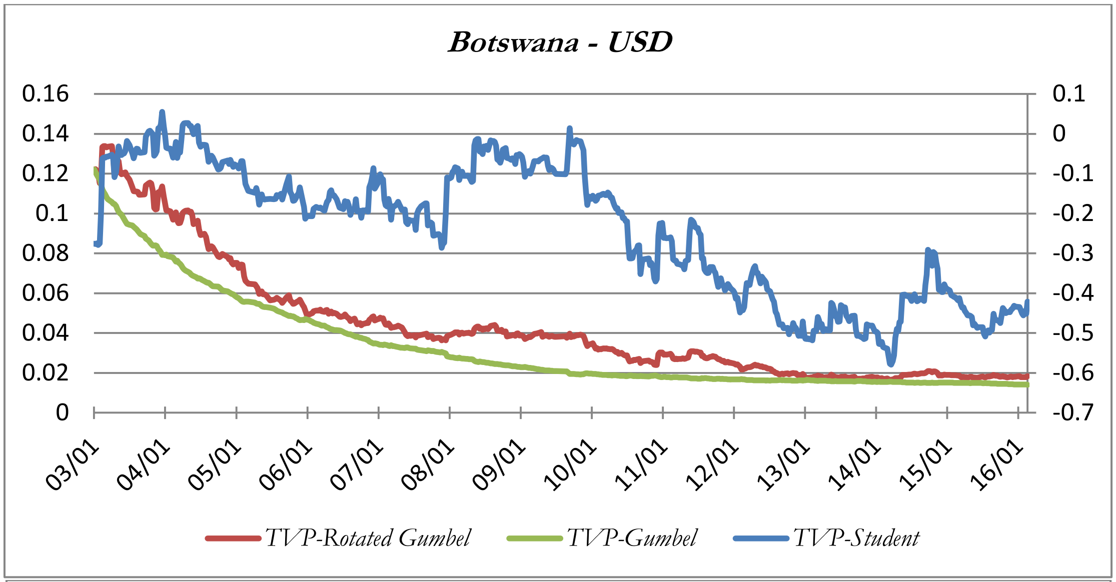


[69] Figures are gleaned from the World Development Indicators database and the website of the African Securities Exchanges Association (ASEA). We could not find figures for 2013 and 2014 for Botswana.


Egypt - USD
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
-0.0482
-0.0483
-0.0484
-0.0485
-0.0486
-0.0487
-0.0488
-0.0489
-0.049
03/01 04/01 05/01 06/01 07/01 08/01 09/01 10/01 11/01 12/01 13/01 14/01 15/01 16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student


South Africa - USD
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0
-0.2
-0.4
-0.6
-0.8
-1
03/01 04/01 05/01 06/01 07/01 08/01 09/01 10/01 11/01 12/01 13/01 14/01 15/01 16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student


Morocco - USD
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
03/01 04/01 05/01 06/01 07/01 08/01 09/01 10/01 11/01 12/01 13/01 14/01 15/01 16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student



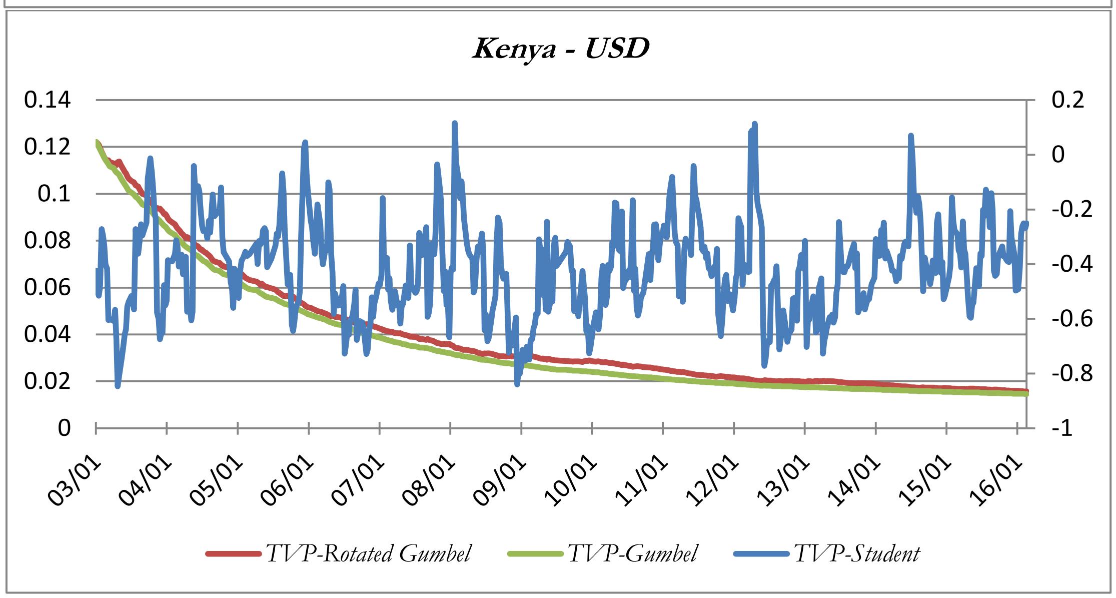


Figure 5.2: Time series plots for parameter estimates of time-varying copulas between African stock markets and foreign exchange rate returns.

Table 5.7 shows the time-varying and static copula model results for the stock market pairs with the EUR exchange rate. Similar to results in Table 5.6, the evidences from both the static and time-varying estimates suggest that, except for Morocco, all equity markets show negative dependence with the EUR exchange rate returns. Significantly, the static Gaussian parameter for the South Africa Rand/USD pair of -0.74 is higher than the South Africa Rand/EUR pair of -0.56. This reflects the higher transactional uses of the USD in the South African economy relative to the EUR.

It is important to stress that, while cases of same directional movement may imply that as stock prices increased (decreased), local currencies against the EUR may also appreciate (depreciate), the reverse may hold for market pairs with significant negative dependencies. The AIC values suggest that both time-varying and static copulas characterize the dependence structure between the stocks and EUR exchange rate. The dependence of each of the Nigerian and Moroccan pairs with the EUR exchange rate is properly fitted by the static lower-tail rotated-Gumbel copula; that of each of Kenya and South Africa are individually best fitted by the TVP student-t copula, and each of Egypt and Botswana by the TVP-Gaussian. These results show evidence of non-uniform coupling of extreme dependencies between the African stock market returns and returns of the EUR exchange rate (see also Reboredo *et al.,* 2016).

In Tables 5.6 and 5.7, the dynamics of dependence measures between returns series for the time-varying (TVP) Gaussian copula are captured by the co-efficients, ψ_1 and ψ_2 in the evolution equation. For all market pairs, we observe high dominance of the time variation effect since the persistence co-efficient, ψ_2 is relatively greater than the variation co-efficient, ψ_1. The inference is that, changes in the dependence structure across all pairs will be better captured by the time-varying copulas for the sample period. We present the time path of dependence measures of all possible pairs of six African stocks in Panels *a* and *b* of Figure 5.2 for all time-varying copula distributions except the TVP-Gaussian over the sample period, to describe how the dependence strength behaves through time.[70]

In all figures, the dependence appears to be more heterogeneous (both on average and at the tails). The TVP-student *t* measures the average dependence, while the TV-Gumbel and Rotated-Gumbel copulas indicate the tails. A common observation across all graphs shows fast-reducing upper and lower-tail dependencies of all markets with the USD and EUR exchange rates over time, except for South Africa Rand/USD pair where there was a sudden sharp increase in upper tail dependence around 2010 and 2011; and the Moroccan Dirham/EUR pair where the graphs depict average signs of mean-reversion over time. The non-homogenous nature of the time-varying correlations usually moving from positive to negative (averagely very low, i.e. less than 0.5) suggests the equity markets partial segmentation from price risks of the exchange rate similar to Kodongo and Ojah (2011).

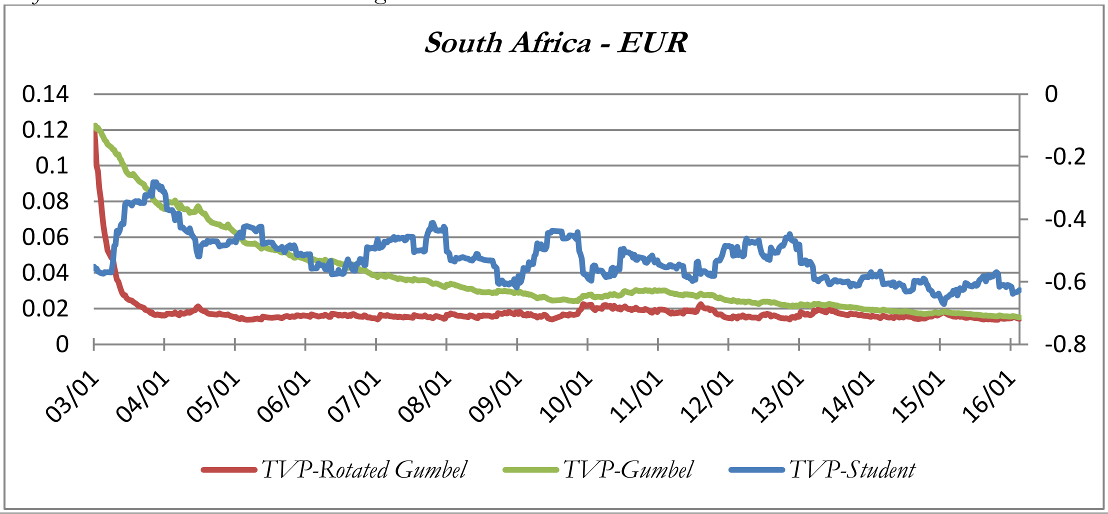
[70] We exclude the TVP-Gaussian because the time-varying Student-t gives almost the same parameter evolution.

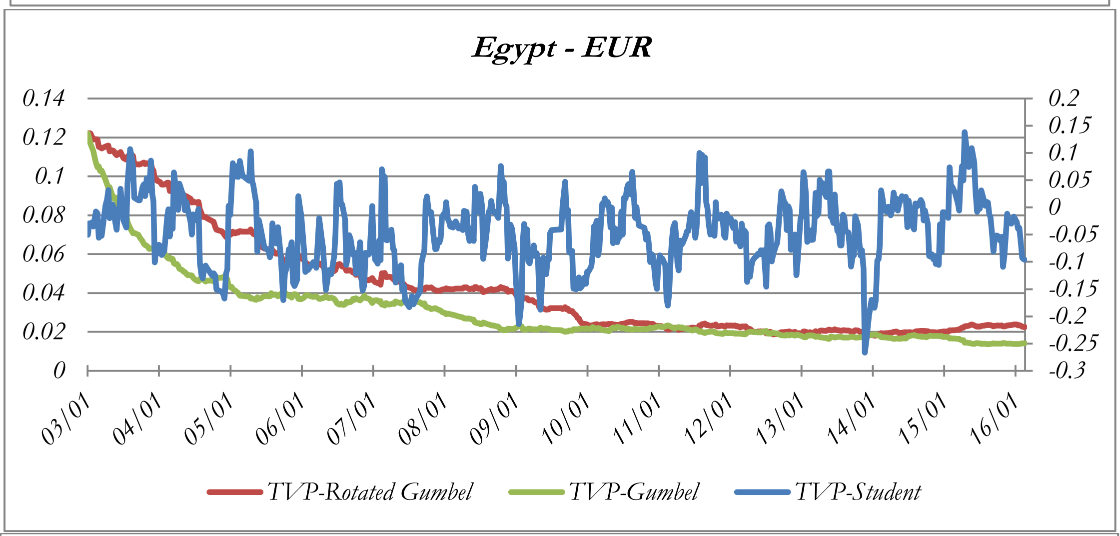
Table 5.7: Bivariate copula model estimates for African stock market and EUR exchange rate returns

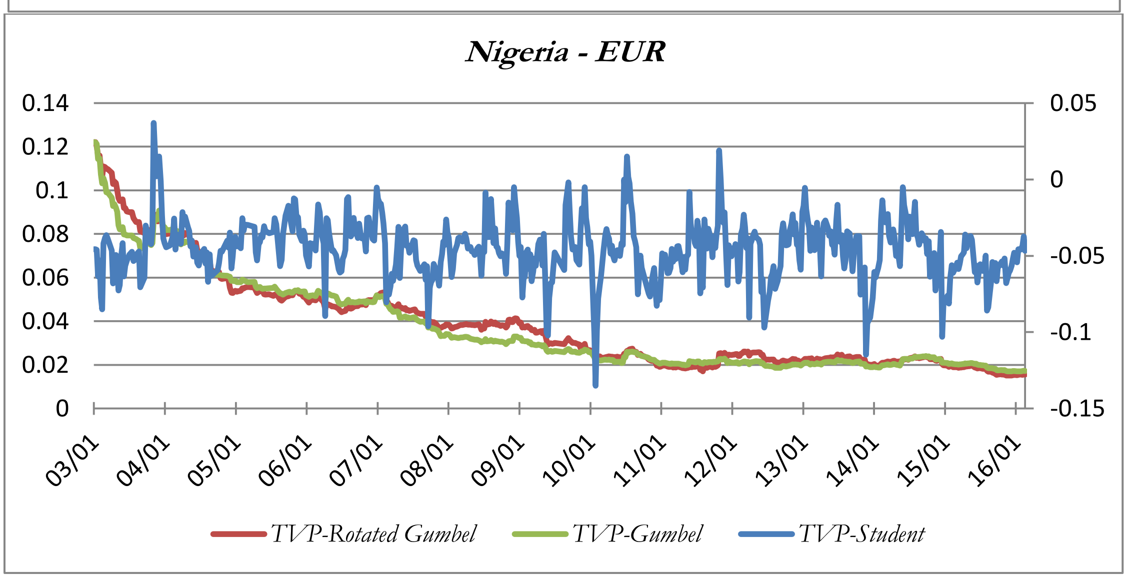
	Kenya	South Africa	Egypt	Nigeria	Morocco	Botswana
Panel A: Time-invariant copulas						
Gaussian						
ρ	-0.122*	-0.562*	-0.052	-0.046	0.365*	-0.113*
	[0.036]	[0.022]	[0.040]	[0.040]	[0.031]	[0.038]
AIC	-7.884	-251.000	0.244	0.594	-92.780	-6.448
Student-t copula						
ρ	-0.020*	-0.568*	-0.060	-0.043	0.364*	-0.117*
	[0.041]	[0.027]	[0.044]	[0.044]	[0.036]	[0.043]
ν	9.929*	9.921*	199.333*	35.781*	13.816*	198.57*
	[4.966]	[2.606]	[0.193]	[1.453]	[1.508]	[3.291]
AIC	-12.588	-258.349	0.727	0.159	-95.575	-6.114
Gumbel						
δ	1.000*	1.000*	1.000*	1.000*	1.258*	1.000*
95% CI	(0.960-1.040)	(0.955-1.045]	(0.954-1.046)	(0.965-1.035)	(1.192-1.324)	(0.954-1.046)
AIC	34.353	106.691	28.732	21.956	-69.938	39.018
Rotated Gumbel						
δ	1.000*	1.000*	1.000*	1.000*	1.301*	1.000*
95% CI	(0.956-1.045)	(0.955-1.045)	(0.958-1.042)	(0.959-1.041)	[1.227-1.374]	(0.958-1.042)
AIC	36.913	106.804	30.363	**-28.083**	**-103.545**	38.886
Panel B: Time-varying copulas						
TVP-Gaussian						
ψ_1	0.059*	0.017*	0.039	0.014	0.000	0.040*
	[0.025]	[0.008]	[0.027]	[0.028]	[0.003]	[0.021]
ψ_2	0.854*	0.983*	0.840*	0.682*	0.585	0.853*
	[0.066]	[2.20E-06]	[0.078]	[0.165]	[2.762]	[0.056]
AIC	-16.962	-255.825	**-0.519**	2.320	-90.764	**-9.171**
TVP-Student						
ψ_0	11.184*	9.967*	199.940*	36.651	13.778	199.86*
	[5.935]	[3.709]	[0.015]	[30.947]	[9.344]	[8.041]
ψ_1	0.057*	0.019*	0.039	0.013	0.000	0.040*
	[0.024]	[0.007]	[0.027]	[0.027]	[0.027]	[0.021]
ψ_2	0.867*	0.981*	0.840*	0.690*	0.633	0.854*
	[0.064]	[2.00E-06]	[0.007]	[0.171]	[0.502]	[15.362]
AIC	**-18.777**	**-261.043**	1.772	3.901	-91.550	-7.036
TVP-Gumbel						
ω	-0.018	-0.027	-0.037	-0.016	-0.052	-0.015
	[0.052]	[0.000]	[0.030]	[0.047]	[0.259]	[0.030]
α	-0.005	-0.015	-0.028	0.025	0.010	0.037
	[0.103]	[0.062]	[0.051]	[0.094]	[0.139]	[0.074]
β	0.996*	0.996*	0.992*	0.996*	0.960*	0.996*
	[0.014]	[0.103]	[0.087]	[0.014]	[0.195]	[0.008]
AIC	14.710	30.392	8.596	9.024	-66.108	13.124
TVP-Rotated Gumbel						
ω	-0.018	-0.269*	-0.016	-0.017	-0.293	-0.014
	[0.000]	[0.003]	[0.208]	[0.000]	[0.243]	[0.000]
α	-0.002	-0.041*	0.018	0.027	0.090	0.042
	[0.007]	[0.021]	[0.063]	[0.040]	[0.125]	[0.626]
β	0.996*	0.943*	0.996*	0.996*	0.754*	0.996*
	[0.001]	[0.078]	[0.070]	[0.002]	[0.200]	[0.035]
AIC	14.924	19.510	10.501	10.813	-100.306	14.568

Notes: See notes on Table 5.6.

Panel B: African stock market and EUR exchange returns







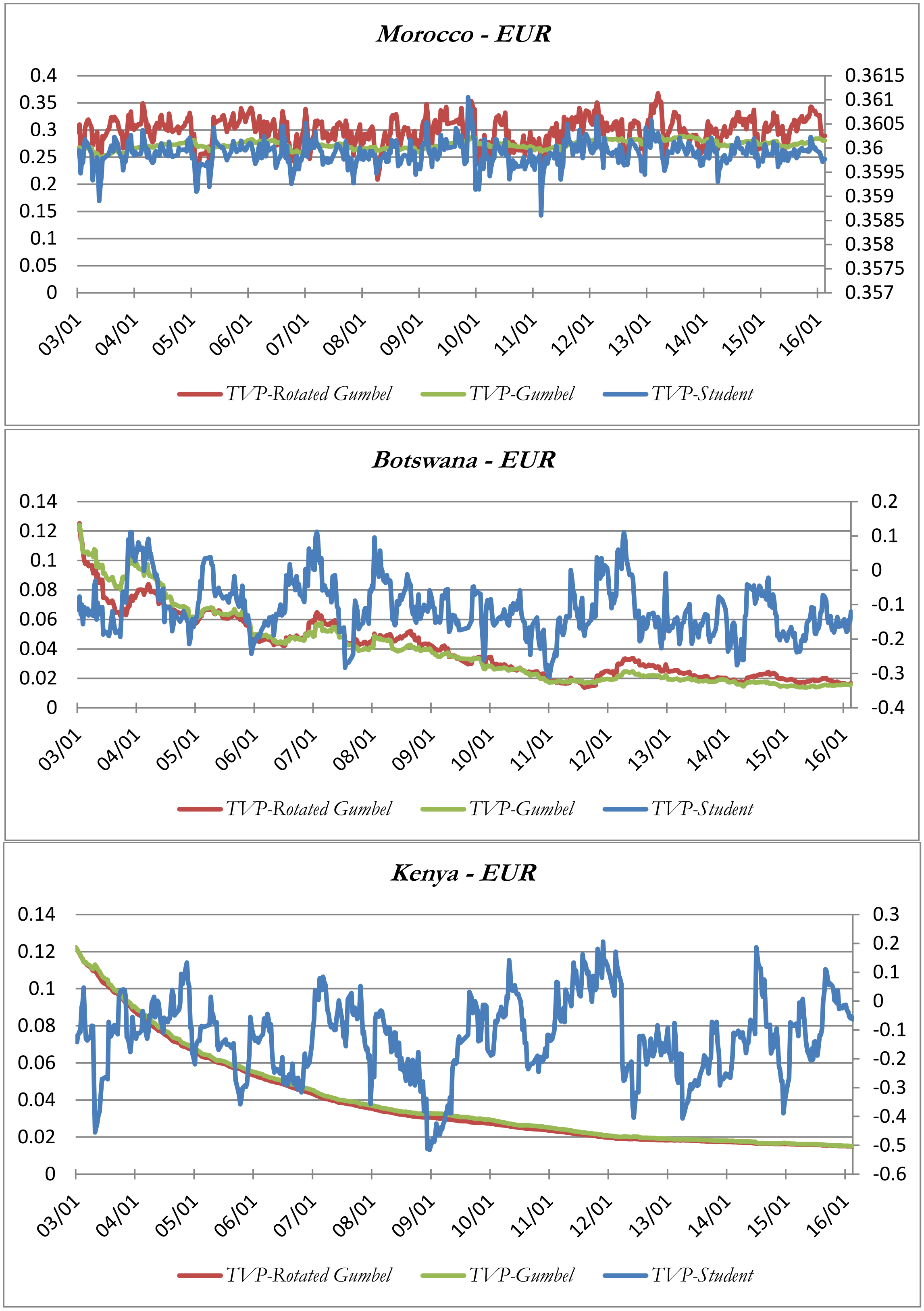


Figure 5.2 (continues)

5.3.3.2 African and developed stock markets

Similar to sub-section 5.3.3.1, we examine the dependence structure between African and developed stock markets using both static and time-varying stochastic copulas. Results are presented in Tables 5.8-5.11. For each market pair, the best fit copulas based on AICs are indicated in bold. Except for Egypt, we find evidence of positive and significant dependencies between all African markets and their developed counterparts. In the case of constant tail dependence; first, all market pairs exhibit both lower and upper tail dependences (as shown by the rotated Gumbel and Gumbel parameters, respectively). This dependency structure suggests that African stock markets stand to lose (gain) in bear (bull) seasons of the developed markets. This rather condenses potential gains from diversification. Another observation is that, for all tables, the lower (left-tail) dependences are higher than the upper (right-tail) dependences for most market pairs. For example, the lower (upper) tail dependence measure for the Kenya-Asia ex-J pair is 1.079 (1.028) – Table 5.8; South Africa-EUSTX pair is 1.787 (1.750) – Table 5.9; or Morocco-FTSE100 pair is 1.151 (1.142) – Table 5.10, etc. This result implies that, although the markets show significant evidence of bear and bull co-movement, the possibility of joint extreme bear dependence/co-movements is higher than bull seasons with market pairs having these characteristics. The reverse is however, true for market pairs showing higher right tail dependence than left tail dependence, example Nigeria-S&P500, EUSTXX, FTSE100; and Botswana-EUSTXX, FTSE100, S&P500. Additionally, some market pairs, example, Egypt-EUSTX AND Egypt-S&P500 show equal left and right-tail dependence, indicating a balance between dependence in tranquil and turbulent market conditions. Similar findings to our results were observed by Bhatti and Nguyen (2012).

Results of the time-varying copula model parameters shown in Panel B of all Tables reveal some interesting observations worth discussing. In the case of the time-varying (TVP) Gaussian copula, the dynamics of dependence measures between returns series are captured by the co-efficient, ψ_1 and ψ_2 in the evolution equation. For all market pairs, we observe high dominance of the time variation effect since the persistence co-efficient, ψ_2 is relatively greater than the variation co-efficient, ψ_1. The inference is that, changes in the dependence structure across all pairs will be better captured by the time-varying copulas for the studied period.

In the time-varying setting, the dependence structure (left- or right-tail) shown is quite similar to that shown in the static framework for all market pairs. The significant similarity is that, in both static and time-varying frameworks, all market pairs show higher persistent time-varying volatility in both left and right tail dependence, since mostly the persistence dependence parameters, β is significant, but the α is non-significant, largely. We present the time path of time-varying dependence measures of all possible pairs of six African stocks in Panels *a-d* of Figure 5.3 for all copula distributions except the TVP-Gaussian.

In all, the South Africa market pairs show distinctive features. It can be observed that the time path of the TVP-Rotated Gumbel copula of South Africa-Asia ex.J, and all other pairs is close to white noise. The TVP-Gumbel, TVP-Rotated Gumbel, and TVP-Student *t* generally fluctuate around a constant copula parameter with varying ranges for all four developed markets pairs with South Africa. These notwithstanding, some pairs' time paths appear to be informative for analysis. The Egypt-Asia ex.J time path did not show much upper and lower tail dependence between 2004 and 2015. In mid-2003, the highest upper (lower) tail dependence was 0.16 (0.13), dropped drastically to a low of 0.018 (0.02) in mid-2006 and reached highs of 0.13 (0.18) in 2015. A similar pattern is observed for both the upper and lower tail dependence measures for the Nigeria-Asia ex.J pairs, with the symmetric tail dependence measure assuming some constancy around 0.15.

Though upper, lower, and average dependence for Botswana-Asia ex.J and Botswana-FTSE appear low from 2003, the dependence structure assumes sharp rises from 2010 from a low of 0.05 to 3.2 in 2012 until it begins to decline slowly. There are also some market pairs showing both lower and upper tail dependence with higher volatility of lower tail time path than upper tail time path. Among such market pairs are: Kenya-Asia ex.J, EUSTX, S&P500; and Morocco-S&P500. Others also have lower and upper tail dependence occurring almost in a cluster, example are the pairs of Morocco-Asia ex.J, FTSE100, EUSTX; Botswana-S&P500, EUXTX; South Africa-FTSE100, S&P500, EUXTX; and Nigeria-FTSE100. In a few instances also, either the lower or upper tail dependence or both assume decreasing trends along the sample period. This is observed for the following market pairs: Egypt-EUSTX, S&P500, FTSE100; Kenya-FTSE100; and Nigeria-S&P500. It must be emphasized that the higher peaks of dependences could be observed around the period 2007-2009 and 2009-2011, giving some indication of the effects of the subprime global financial crisis and the European sovereign debt crisis.

Table 5.8: Bivariate copula model estimates for African stock market and Asia ex-J stock returns

	Kenya	South Africa	Egypt	Nigeria	Morocco	Botswana
Panel A: Time-invariant copulas						
Gaussian						
ρ	0.109*	0.676*	0.042	0.152*	0.168*	0.161*
	[0.038]	[0.020]	[0.039]	[0.037]	[0.035]	[0.036]
AIC	-5.846	-407.6	0.848	13.466	16.896	-15.294
Student-t copula						
ρ	0.099*	0.670*	0.037	0.152*	0.168*	0.167*
	[0.044]	[0.023]	[0.043]	[0.042]	[0.041]	[0.041]
ν	67.670	13.884*	198.109*	38.023*	9.860*	25.004*
	[1833.044]	[1.985]	[20.373]	[1.350]	[4.748]	[0.518]
AIC	-5.898	**-411.542**	0.903	**-13.835**	-21.924	-15.685
Gumbel						
δ	1.028*	1.180*	1.009*	1.082*	1.095*	1.094*
95% CI	(0.98-1.08)	(1.68-1.88)	(0.96-1.06)	(1.03-1.14)	(1.04-1.15)	(1.04-1.15)
AIC	7.278	-366.077	13.416	-8.990	-12.068	-10.196
Rotated Gumbel						
δ	1.079*	1.811*	1.029*	1.088*	1.123*	1.106*
95% CI	(1.03-1.13)	(1.70-1.92)	(0.98-1.07)	(1.03-1.14)	(1.07-1.18)	(1.05-1.16)
AIC	-12.004	-392.373	7.861	-9.533	-24.944	-15.021
Panel B: Time-varying copulas						
TVP-Gaussian						
ψ_1	0.035*	0.028	0.012*	0.002	0.039*	0.046*
	[0.016]	[0.021]	[0.007]	[0.006]	[0.018]	[0.006]
ψ_2	0.906*	0.862*	0.988*	0.985*	0.892*	0.979*
	[0.032]	[0.122]	[3.55E-06]	[0.012]	[0.050]	[0.009]
AIC	-10.943	-408.458	**-1.214**	-11.561	-23.289	**-21.363**
TVP-Student						
ψ_0	103.611	14.129*	198.330*	40.763	10.936*	74.227
	[97877.410]	[7.357]	[8.519]	[75.047]	[5.746]	[67.631]
ψ_1	0.035*	0.024	0.012*	0.001	0.040*	0.014*
	[0.016]	[0.018]	[0.007]	[0.007]	[0.018]	[0.006]
ψ_2	0.906*	0.888*	0.988*	0.985*	0.885*	0.979*
	[0.032]	[0.078]	[3.11E-06]	[0.012]	[0.051]	[0.009]
AIC	-9.000	-410.128	0.814	-9.923	-25.601	-19.437
TVP-Gumbel						
ω	-0.057	-0.065	-0.006	0.028*	-0.123*	-0.021*
	[0.042]	[0.052]	[0.010]	[0.011	[0.044]	[0.010]
α	0.155	0.146	-0.085*	0.085	0.240*	0.093*
	[0.130]	[0.102]	[0.044]	[0.085]	[0.082]	[0.051]
β	0.979*	0.740*	0.996*	0.990*	0.952*	0.990*
	[0.013]	[0.183]	[0.003]	[0.001]	[0.017]	[0.012]
AIC	3.424	-372.686	3.976	-7.256	-15.470	-12.715
TVP-Rotated Gumbel						
ω	-0.082*	0.000	0.001	-0.047	-0.133*	-0.010
	[0.016]	[0.000]	[0.017]	[0.080]	[0.026]	[0.089]
α	0.231*	0.003	0.098	0.087	0.198*	0.071
	[0.071]	[0.004]	[0.125]	[0.057]	[0.082]	[0.084]
β	0.969*	0.999*	0.998*	0.982*	0.942*	0.994*
	[0.005]	[0.012]	[0.005]	[0.031]	[0.001]	[0.038]
AIC	**-16.627**	-393.918	-0.890	-7.102	**-26.832**	-18.832

Notes: The table shows results of static/time-invariant and time-varying bivariate copula models for African stock markets and Asia ex-J stock returns. CI is confidence interval. For other notations and details see notes on Table 4.6.

Table 5.9: Bivariate copula model estimates for African stock market and EUSTXX stock returns

	Kenya	**South Africa**	**Egypt**	**Nigeria**	**Morocco**	**Botswana**
Panel A: Time-invariant copulas						
Gaussian						
ρ	0.122*	0.662*	-0.011	0.106*	0.271*	0.193*
	[0.039]	[0.020]	[0.040]	[0.037]	[0.035]	[0.036]
AIC	-7.924	-385.000	**1.921**	5.518	-48.56	-23.040
Student-t copula						
ρ	0.113*	0.663*	-0.024	0.114*	0.265*	0.196*
	[0.044]	[0.023]	[0.044]	[0.042]	[0.040]	[0.040]
v	198.693*	11.847*	199.035*	41.068	15.006	22.480
	[5.828]	[5.432]	[1.636]	[87.064]	[10.114]	[26.178]
AIC	-7.724	-390.516	2.496	-5.613	-50.767	-23.743
Gumbel						
δ	1.039*	1.750*	1.000*	1.063*	1.176*	1.127*
95% CI	(0.99-1.09)	(1.65-1.85)	(0.96-1.04)	(1.01-1.12)	(1.12-1.24)	(1.07-1.19)
AIC	4.270	-344.228	21.974	-2.511	-40.572	-19.832
Rotated Gumbel						
δ	1.079*	1.787*	1.000*	1.058*	1.192*	1.121*
95% CI	(1.03-1.13)	(1.68-1.90)	(0.96-1.04)	(1.01-1.11)	(1.13-1.16)	(1.06-1.18)
AIC	**-11.373**	-374.450	21.915	-1.277	-49.504	-19.976
Panel B: Time-varying copulas						
TVP-Gaussian						
ψ_1	0.022	0.070*	5.23e-06	2.55e-06	0.037*	0.034
	[0.017]	[0.020]	[3.23e-05]	[2.29e-06]	[0.010]	[0.017]
ψ_2	0.888*	0.839*	0.993*	0.950*	0.878*	0.953*
	[0.035]	0.040]	[0.016]	[0.089]	[0.061]	[0.044]
AIC	-7.609]	-405.930	3.922	-3.516	-51.510	**-30.055**
TVP-Student						
ψ_0	199.439*	20.577	199.557*	47.517	25.788	33.867
	[2.366]	[15.751]	[0.301]	[328.350]	[26.209]	[32.004]
ψ_1	0.022	0.068*	2.88e-05	9.29e-07	0.034	0.025
	[0.017]	[0.021]	[0.008]	[1.50e-06]	[0.022]	[0.019]
ψ_2	0.888*	0.843*	0.990*	0.920*	0.871*	0.951*
	[0.035]	[0.042]	[0.103]	[0.112]	[0.071]	[0.053]
AIC	-5.530	**-406.562**	6.080	-1.744	-50.252	-28.431
TVP-Gumbel						
ω	-0.252	-0.042*	-0.060	-0.132*	-0.110*	-0.777
	[0.251]	[0.010]	[0.000]	[0.018]	[0.014]	[0.491]
α	0.202*	0.181*	-0.078	-0.261*	0.183*	0.558*
	[0.109]	[0.068]	[0.010]	[0.130]	[0.101]	[0.062]
β	0.918*	0.860*	0.986*	0.957*	0.941*	0.661*
	[0.071]	[0.031]	[0.004]	[0.001]	[0.008]	[0.203]
AIC	2.840		8.081]	-5.524	-44.656	-26.090
TVP-Rotated Gumbel						
ω	-0.151*	-0029*	-0.032	-0.083	-0.102*	-0.178
	[0.058]	[0.006]	[0.025]	0.076	[0.020]	[0.267]
α	0.131*	0.155*	-0.021	-0.204*	0.261*	0.177
	[0.085]	[0.048]	[0.084]	0.034	[0.074]	[0.138]
β	0.943*	0.886*	0.993*	0.974*	0.945*	0.915*
	[7.342]	[0.002]	[0.007]	0.008	[0.011]	[0.127]
AIC	-8.684	22.456	8.804	**-6.098**	**-59.267**	-24.121

Notes: The table shows results of static/time-invariant and time-varying bivariate copula models for African stock markets and EUSTXX stock returns. CI is confidence interval. For other notations and details, see notes on Table 4.6.

Table 5.10: Bivariate copula model estimates for African stock market and FTSE 100 stock returns

	Kenya	South Africa	Egypt	Nigeria	Morocco	Botswana
Panel A: Time-invariant copulas						
Gaussian						
ρ	0.125*	0.708*	0.002	0.101*	0.231*	0.199*
	[0.040]	[0.018]	[0.039]	[0.037]	[0.037]	[0.034]
AIC	-8.404	-465.2	**1.998**	-4.826	-34.320	-24.96
Student-t copula						
ρ	0.112*	0.710*	-0.009	0.106*	0.222*	0.209*
	[0.045]	[0.020]	[0.043]	[0.042]	[0.043]	[0.039]
v	199.176*	9.167*	66.845	19.047	17.734*	11.869*
	[6.975]	[3.306]	[40.442]	[21.56]	[1.261]	[5.773]
AIC	-7.992	**-474.837**	2.048	**-6.141**	-35.923	-28.182
Gumbel						
δ	1.033*	1.879*	1.001*	1.060*	1.142*	1.137*
95% CI	(0.98-1.08)	(1.77-1.99)	(0.96-1.04)	(1.01-1.11)	(1.08-1.20)	(1.08-1.20)
AIC	5.936	-420.239	18.435	-2.887	-31.436	-23.155
Rotated Gumbel						
δ	1.080*	1.933*	1.000*	1.059*	1.151*	1.132*
95% CI	(1.03-1.14)	(1.82-2.05)	(0.96-1.04)	(1.01-1.11)	(1.09-1.21)	(1.07-1.19)
AIC	**-12.169**	-459.474	19.159	-1.656	-32.112	-22.295
Panel B: Time-varying copulas						
TVP-Gaussian						
ψ_1	0.005	0.021	0.008	4.34e-06	0.059*	0.023*
	[0.013]	[0.018]	[0.022]	[3.60e-05]	[0.031]	[0.011]
ψ_2	0.932*	0.870*	0.876*	0.876*	0.696*	0.965*
	[0.025]	[0.067]	[0.044]	[0.403]	[0.186]	[0.021]
AIC	-6.513	-465.167	3.834	-2.828	**-37.843**	**-36.687**
TVP-Student						
ψ_0	199.881*	9.372*	89.533	19.43	24.314	17.038
	[0.054]	[3.39]	[15596.76]	[19.636]	[21.013]	[11.915]
ψ_1	0.005	0.018	0.008	8.24e-08*	0.056*	0.023*
	[0.013]	[0.017]	[0.022]	[1.47e-15]	[0.013]	[0.011]
ψ_2	0.932*	0.892*	0.876*	0.605*	0.702*	0.966*
	[0.025]	[0.056]	[0.045]	[0.039]	[0.187]	[0.021]
AIC	-4.297	-472.319	5.770	-2.172	-36.789	-36.335
TVP-Gumbel						
ω	-0.044	-0.001	-0.033	-0.114	-0.070	-0.011
	[0.027]	[0.000]	[0.019]	[0.097]	[0.079]	[0.008]
α	-0.061	-0.017*	-0.020	-0.182	0.139	0.084*
	[0.476]	[0.001]	[0.170]	[0.127]	[0.119]	[0.036]
β	0.988*	0.999*	0.993*	0.963*	0.967*	0.994*
	[0.011]	[0.002]	[0.015]	[0.033]	[0.039]	[0.004]
AIC	5.527	-419.481	7.549	-2.563	-30.989	-28.764
TVP-Rotated Gumbel						
ω	-0.118	-0.001	-0.031*	-0.063*	-0.092	-0.020
	[0.468]	[0.000]	[0.015]	[0.031]	[0.091]	[0.045]
α	0.039	-0.045*	-0.020	-0.137	0.184*	0.121*
	[0.464]	[0.002]	[0.097]	[0.191]	[0.087]	[0.090]
β	0.953*	0.992*	0.993*	0.980*	0.954*	0.990*
	[0.199]	[0.001]	[0.005]	[0.001]	[0.051]	[0.019]
AIC	-8.634	-470.276	7.506	-1.190]	-34.578	-28.297

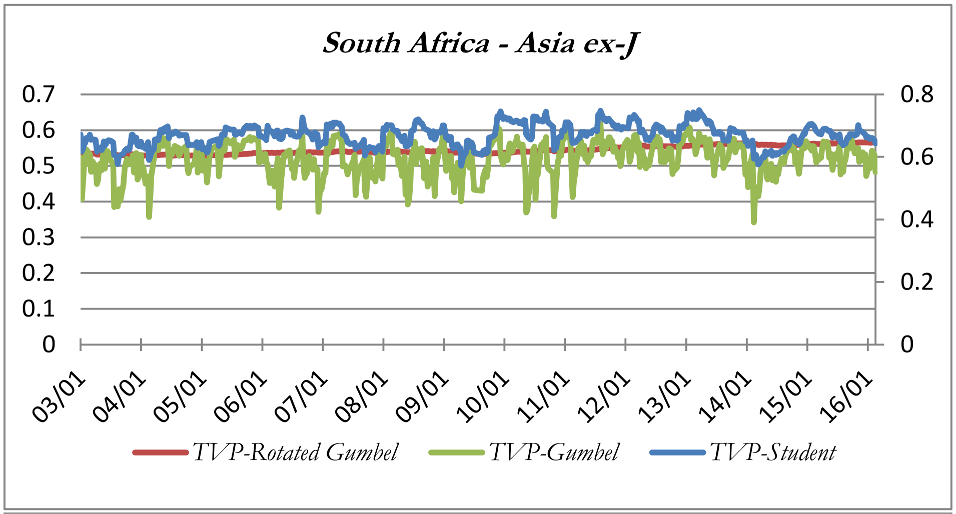
Notes: The table shows results of static/time-invariant and time-varying bivariate copula models for African stock markets and FTSE 100 stock returns. CI is confidence interval. For other notations and details see notes on Table 4.6.

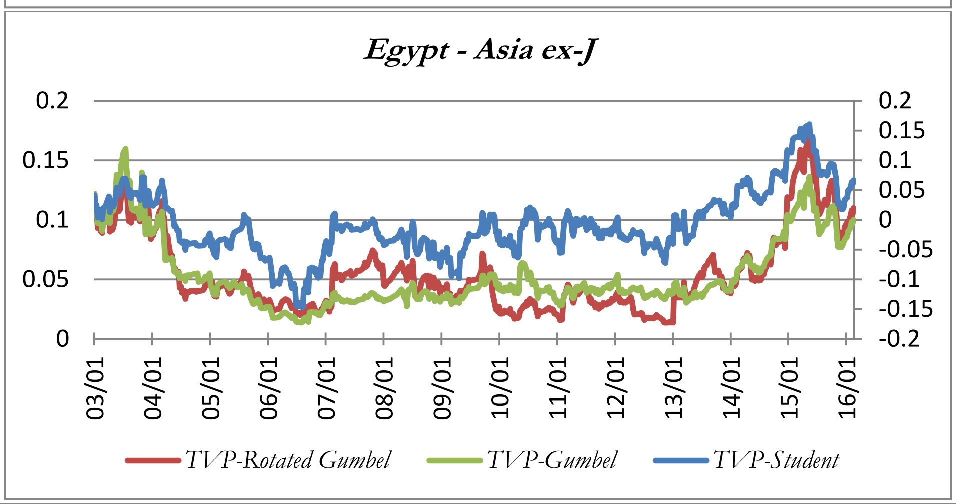
Table 5.11: Bivariate copula model estimates for African stock market and S&P 500 stock returns

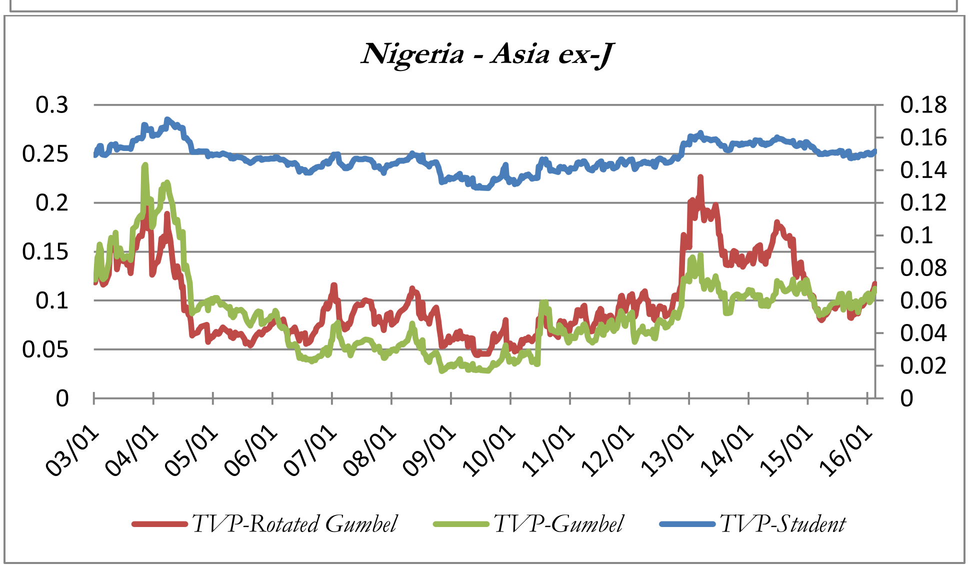
	Kenya	South Africa	Egypt	Nigeria	Morocco	Botswana
Panel A: Time-invariant copulas						
Gaussian						
ρ	0.099*	0.568*	0.020	0.068*	0.136*	0.147*
	[0.040]	[0.024]	[0.038]	[0.018]	[0.036]	[0.035]
AIC	-4.620	-258.6	1.727	1.091	-10.322	-12.482
Student-t copula						
ρ	0.090*	0.572*	0.013	0.079*	0.127*	0.156*
	[0.045]	[0.027]	[0.043]	[0.012]	[0.042]	[0.041]
v	199.208*	7.982*	41.944*	58.281	12.581*	17.018
	[15.042]	[2.774]	[0.969]	[96.214]	[5.891]	[13.681]
AIC	-4.304	-267.713	1.492	-0.917	-13.660	-14.306
Gumbel						
δ	1.033*	1.555*	1.000*	1.060*	1.142*	1.137*
95% CI	(0.98-1.08)	(1.47-1.64)	(0.96-1.04)	(1.01-1.11)	(1.08-1.20)	(1.08-1.20)
AIC	5.936	-231.191	18.435	**-2.887**	-31.436	**-23.155**
Rotated Gumbel						
δ	1.080*	1.585*	1.000*	1.059*	1.151*	1.132*
95% CI	(1.03-1.14)	(1.49-1.68)	(0.96-1.04)	(1.01-1.11)	(1.09-1.21)	(1.07-1.19)
AIC	**-12.169**	-260.899	19.159	-1.656	**-32.112**	-22.295
Panel B: Time-varying copulas						
TVP-Gaussian						
ψ_1	0.010	0.043	0.034	1.09e-05	0.052*	0.023
	[0.015]	[0.036]	[0.024]	[1.98e-05]	[0.025]	[0.021]
ψ_2	0.910*	0.837*	0.855*	0.986*	0.823*	0.895*
	[0.039]	[0.067]	[0.037]	[0.045]	[0.079]	[0.108]
AIC	-3.058	-263.664	**1.134**	0.912	-15.718	-12.946
TVP-Student						
ψ_0	199.991*	8.343*	51.897	82.038*	14.453*	19.91
	[0.001]	[2.929]	[47.036]	[18.037]	[6.688]	[13.422]
ψ_1	0.010	0.045*	0.034	0.000	0.055*	0.023
	[0.015]	[0.023]	[0.024]	[0.006]	[0.025]	[0.020]
ψ_2	0.911*	0.854*	0.854*	0.991*	0.813*	0.887*
	[0.039]	[0.066]	[0.037]	[128.865]	[0.081]	[0.107]
AIC	-0.851	**-270.647**	2.932	2.826	-16.831	-12.387
TVP-Gumbel						
ω	-0.040	-0.102*	-0.033	-0.049	-0.035	-0.926*
	[0.258]	[0.039]	[0.000]	[0.032]	[0.000]	[1.956]
α	0.136	0.119	-0.019	-0.080	-0.076	0.374*
	[0.603]	[0.094]	[0.038]	[0.191]	[0.000]	[0.122]
β	0.988*	0.825*	0.993*	0.987*	0.988*	0.627
	[0.074]	[0.063]	[0.001]	[0.006]	[0.002]	[0.805]
AIC	5.859	-231.218	7.118	5.772	-6.339	-7.911
TVP-Rotated Gumbel						
ω	-0.167*	-0065	-0.025	-0.045	-0.160*	-0.674
	[0.079]	[0.055]	[0.033]	[0.059]	[0.029]	[0.568]
α	0.149*	0.055	-0.010	0.117	0.187*	0.347*
	[0.060]	[0.055]	[0.548]	[0.210]	[0.029]	[0.152]
β	0.943*	0.878*	0.994*	0.986	0.934*	0.736*
	[0.031]	[0.108]	[0.033]	[0.021]	[0.010]	[0.228]
AIC	-2.621	-258.101	5.606	2.888	-17.599	-9.552

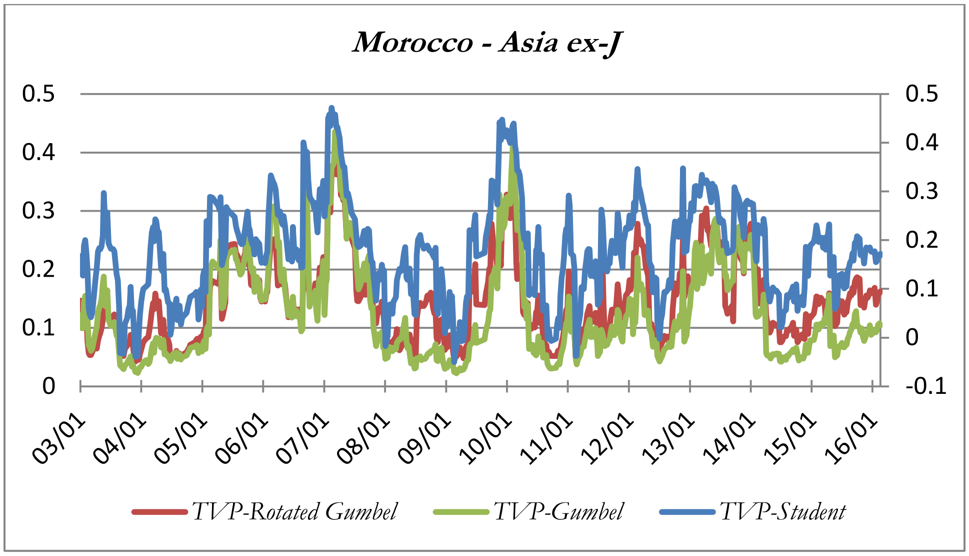
Notes: The table shows results of static/time-invariant and time-varying bivariate copula models for African stock markets and S&P 500 stock returns. CI is confidence interval. For other notations and details see notes on Table 4.6.

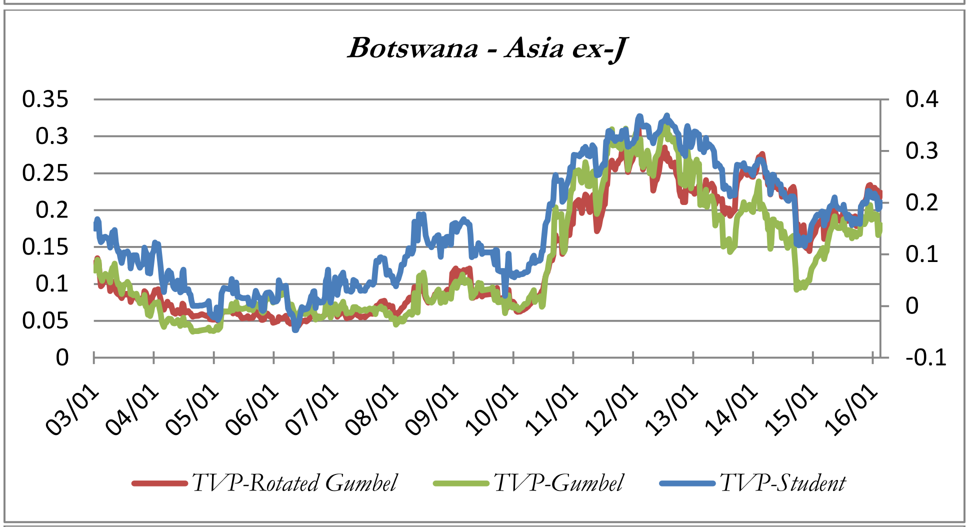
Panel A: African stock market and Asia ex-J returns.

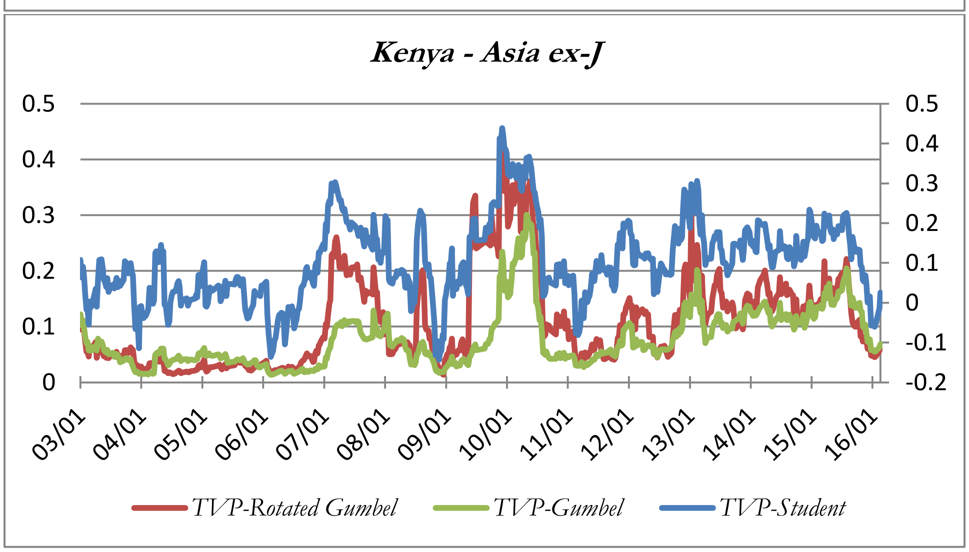




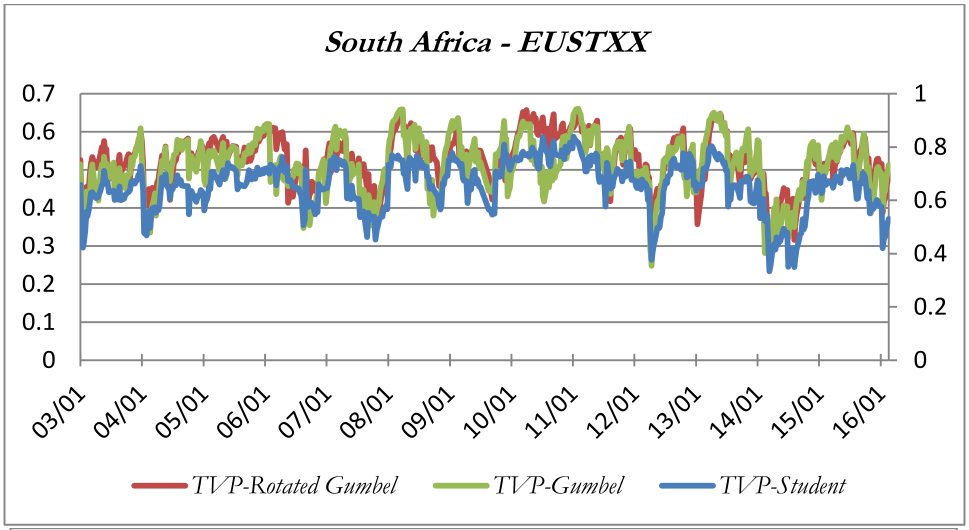


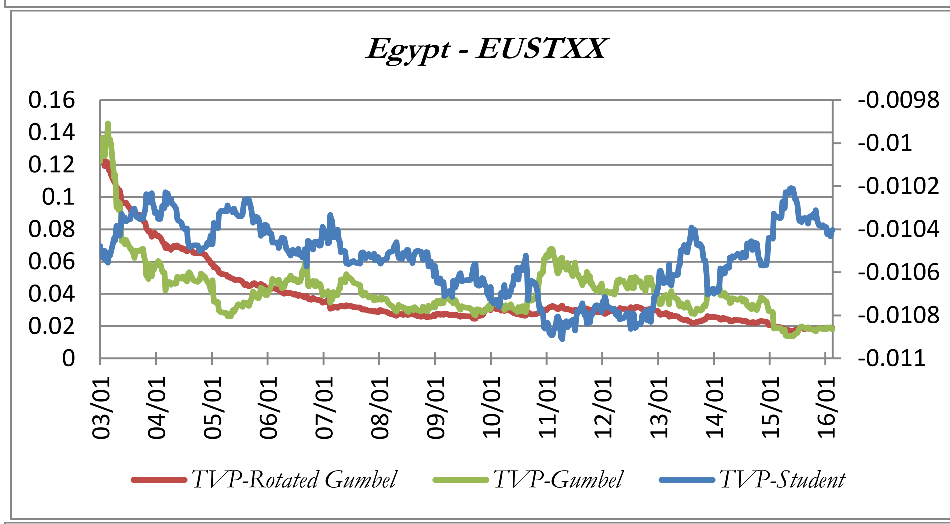

Morocco - Asia ex-J
0.5
0.4
0.3
0.2
0.1
0
0.5
0.4
0.3
0.2
0.1
0
-0.1
03/01 04/01 05/01 06/01 07/01 08/01 09/01 10/01 11/01 12/01 13/01 14/01 15/01 16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student

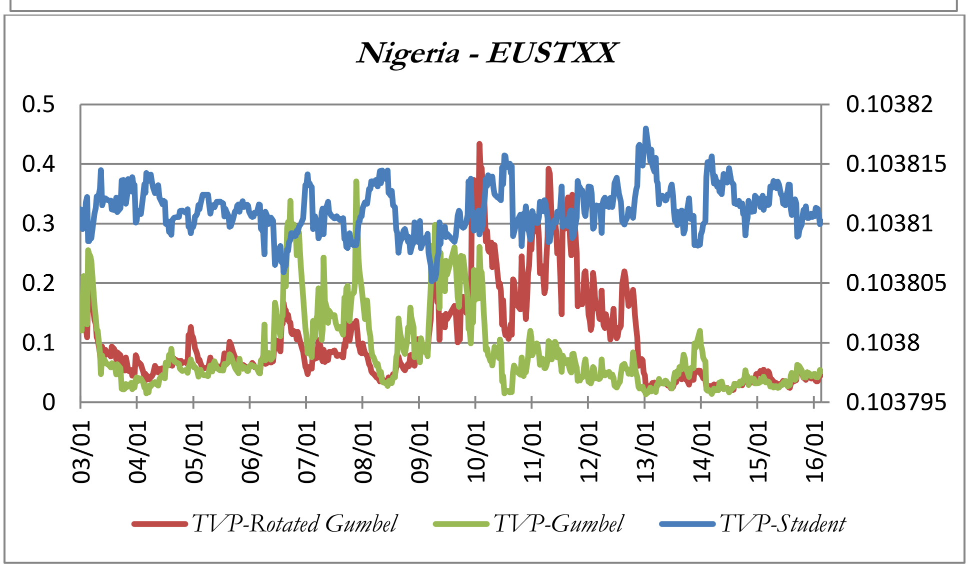

Botswana - Asia ex-J
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0.4
0.3
0.2
0.1
0
-0.1
03/01 04/01 05/01 06/01 07/01 08/01 09/01 10/01 11/01 12/01 13/01 14/01 15/01 16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student

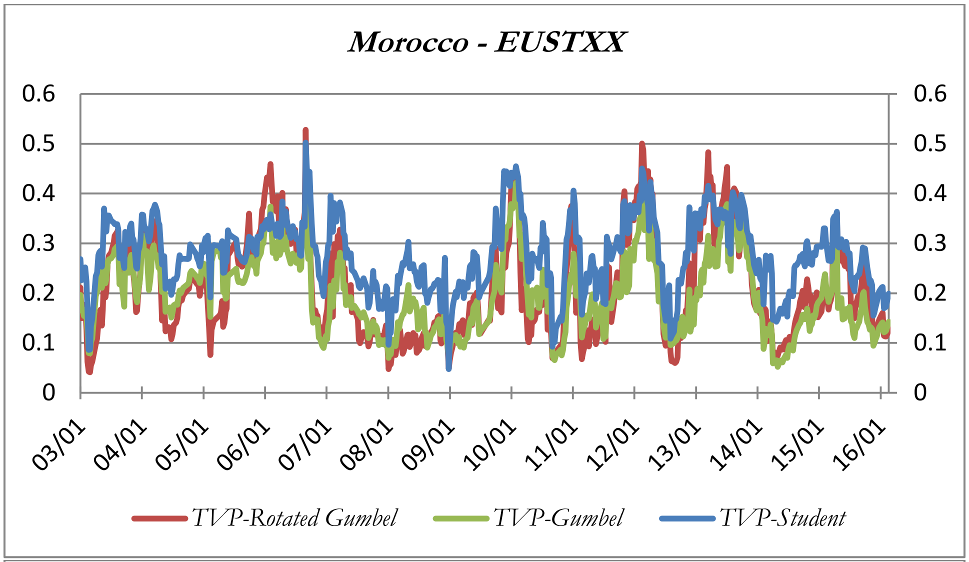

Kenya - Asia ex-J
0.5
0.4
0.3
0.2
0.1
0
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
03/01 04/01 05/01 06/01 07/01 08/01 09/01 10/01 11/01 12/01 13/01 14/01 15/01 16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student

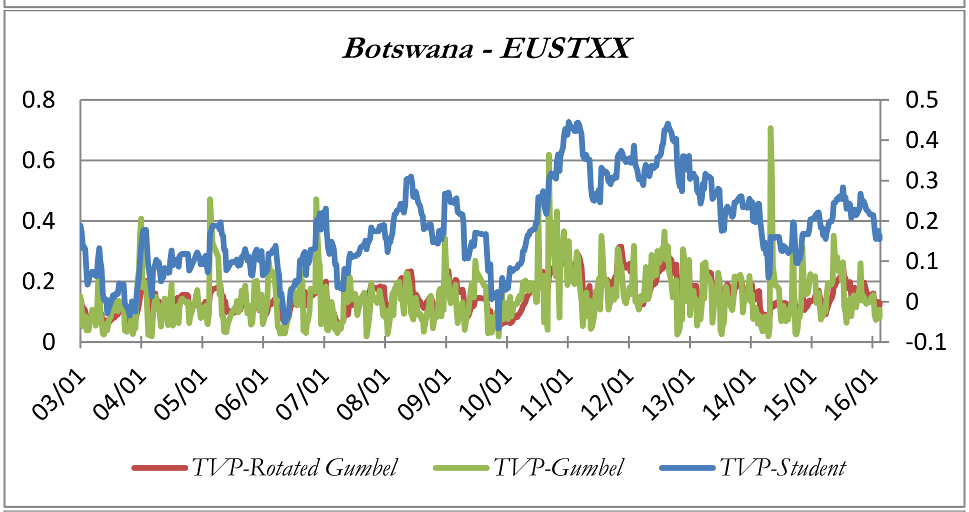
Panel B: African stock market and EUSTXX returns

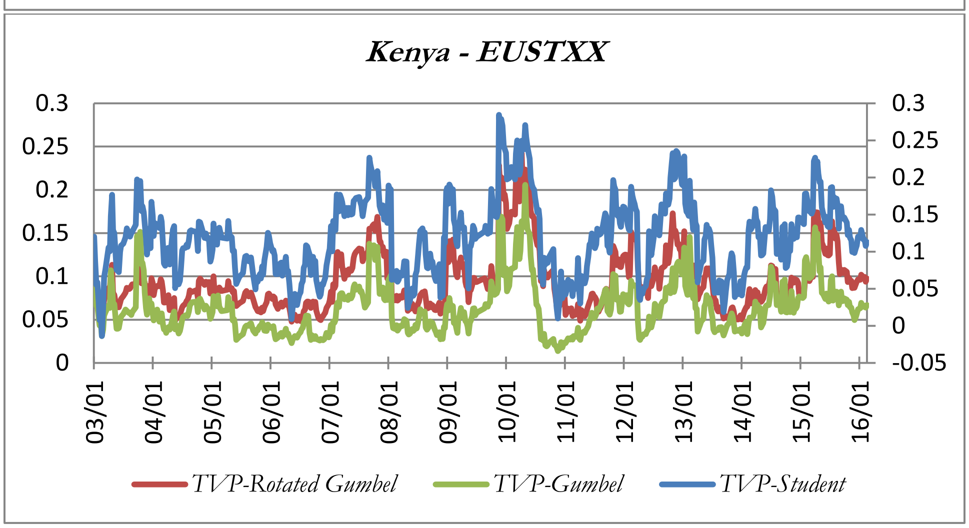




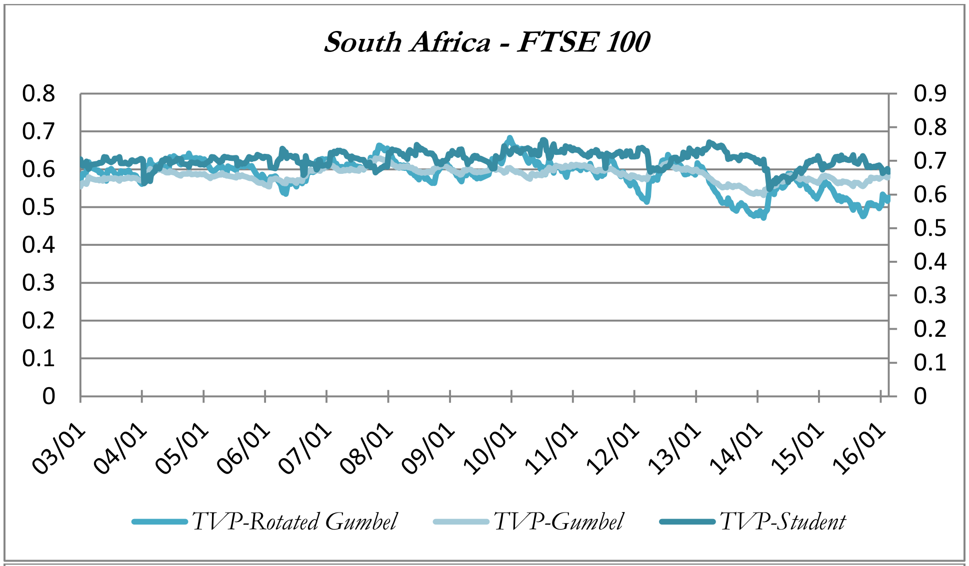


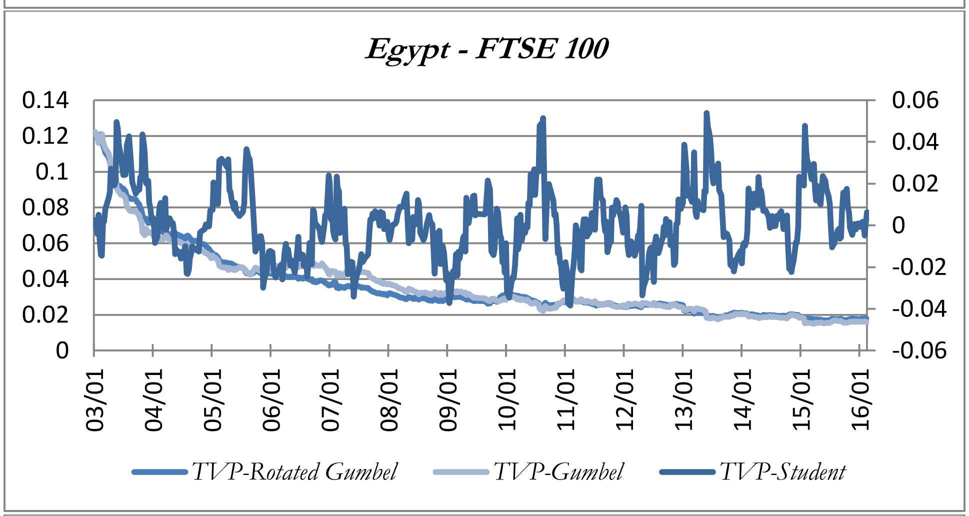

Morocco - EUSTXX
0.6
0.5
0.4
0.3
0.2
0.1
0
03/01
04/01
05/01
06/01
07/01
08/01
09/01
10/01
11/01
12/01
13/01
14/01
15/01
16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student

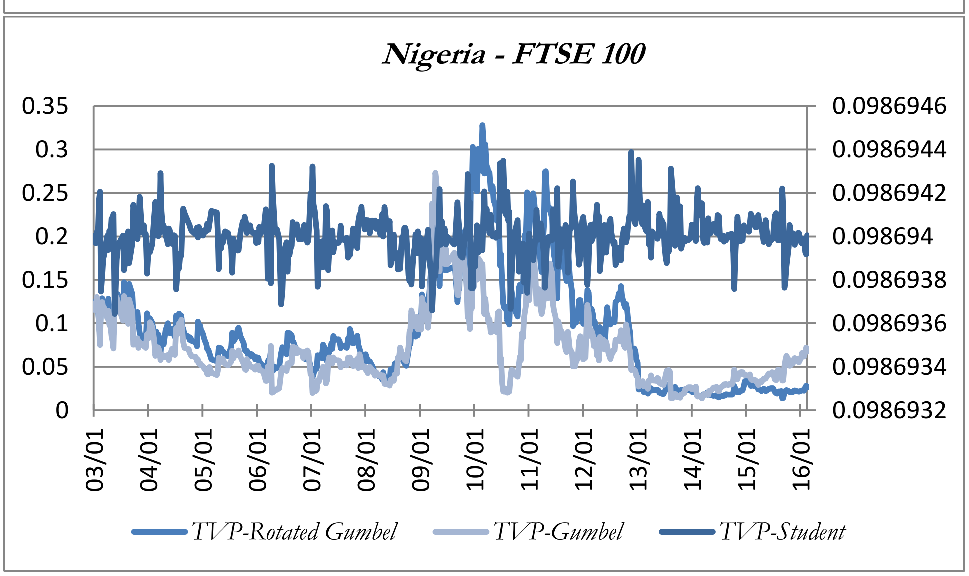

Botswana - EUSTXX
0.8
0.6
0.4
0.2
0
0.5
0.4
0.3
0.2
0.1
0
-0.1
03/01
04/01
05/01
06/01
07/01
08/01
09/01
10/01
11/01
12/01
13/01
14/01
15/01
16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student

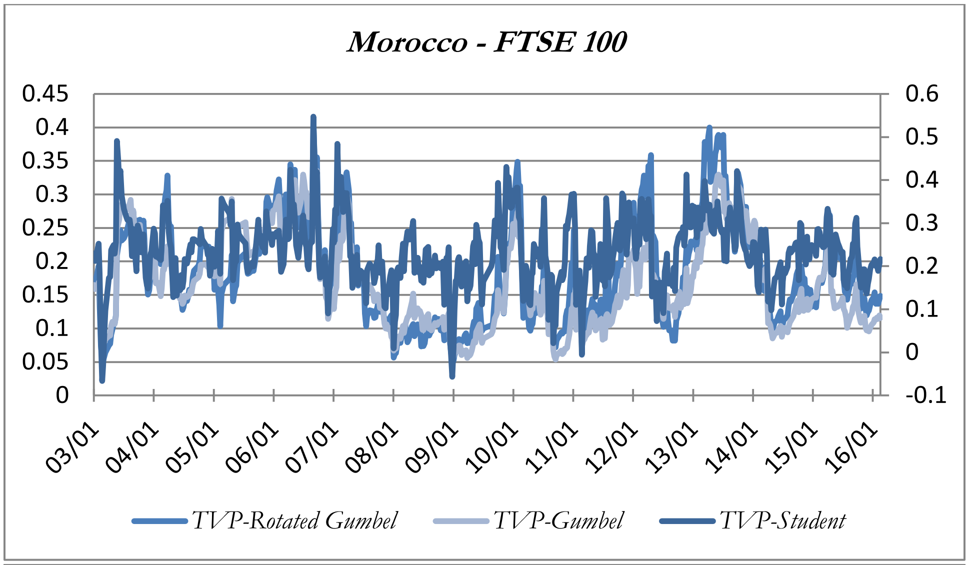

Kenya - EUSTXX
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
03/01
04/01
05/01
06/01
07/01
08/01
09/01
10/01
11/01
12/01
13/01
14/01
15/01
16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student

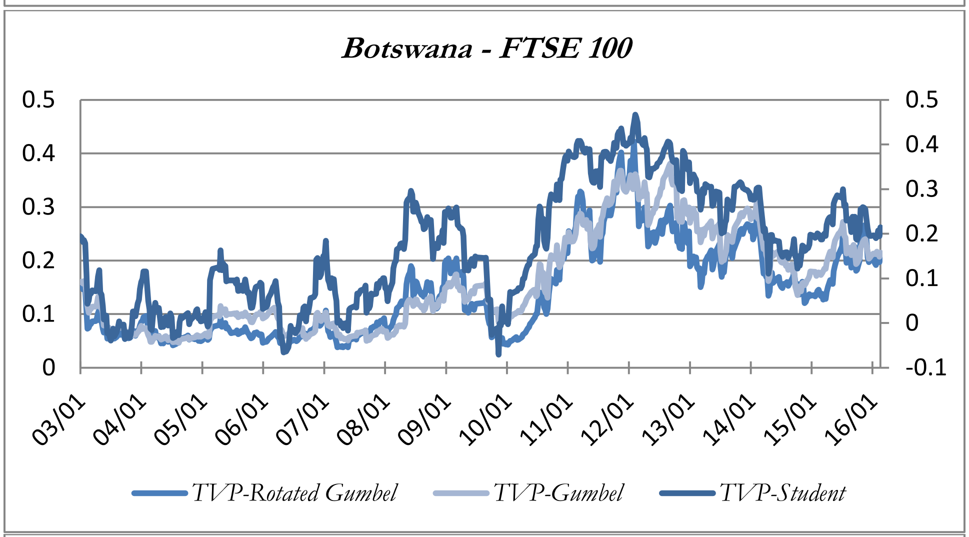
Panel C: African stock market and FTSE 100 returns

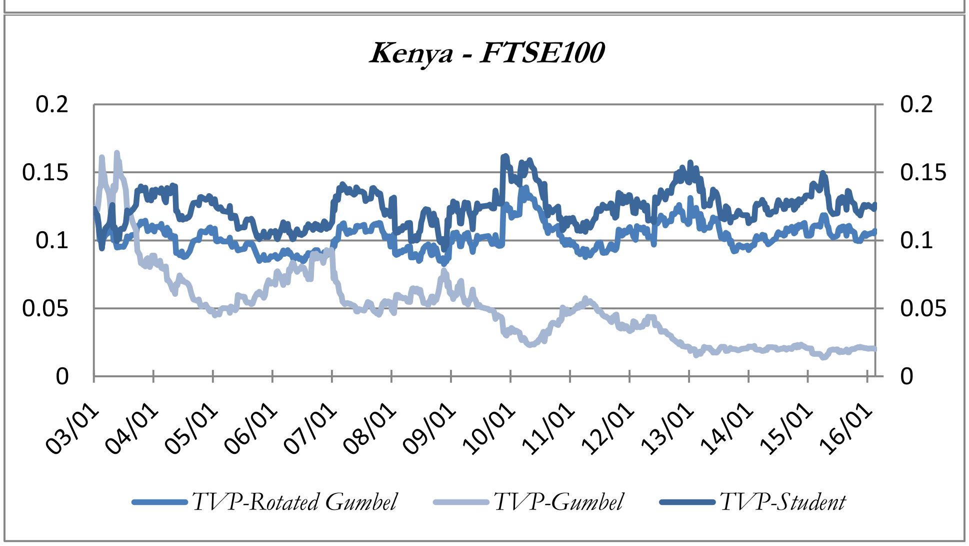




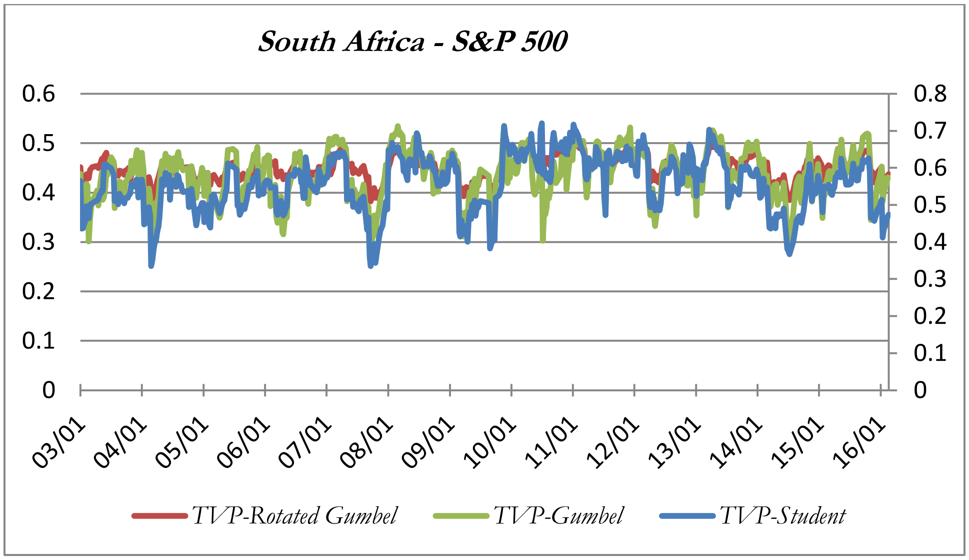


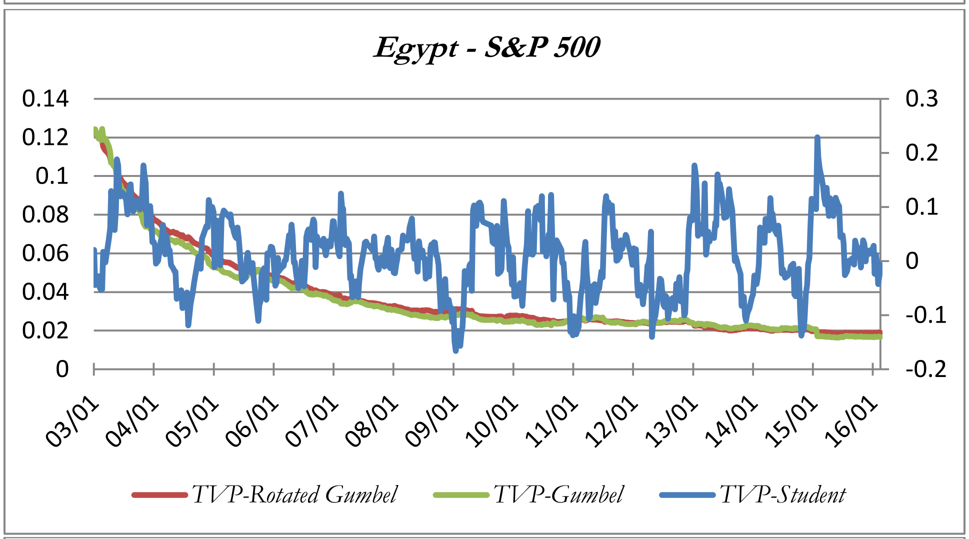

Morocco - FTSE 100
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
03/01 04/01 05/01 06/01 07/01 08/01 09/01 10/01 11/01 12/01 13/01 14/01 15/01 16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student

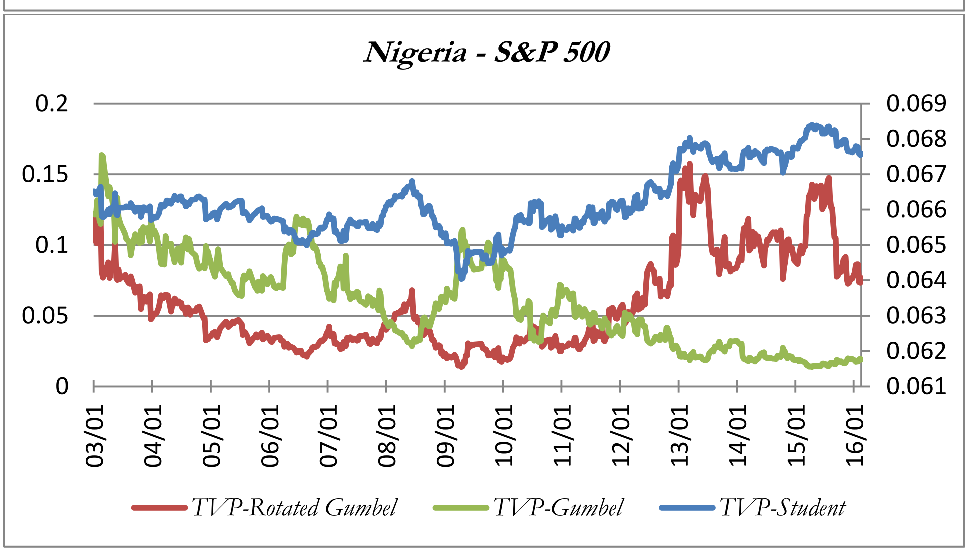

Botswana - FTSE 100
0.5
0.4
0.3
0.2
0.1
0
0.5
0.4
0.3
0.2
0.1
0
-0.1
03/01 04/01 05/01 06/01 07/01 08/01 09/01 10/01 11/01 12/01 13/01 14/01 15/01 16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student


Kenya - FTSE100
0.2
0.15
0.1
0.05
0
0.2
0.15
0.1
0.05
0
03/01 04/01 05/01 06/01 07/01 08/01 09/01 10/01 11/01 12/01 13/01 14/01 15/01 16/01
TVP-Rotated Gumbel
TVP-Gumbel
TVP-Student

Panel D: African stock market and S&P 500 returns







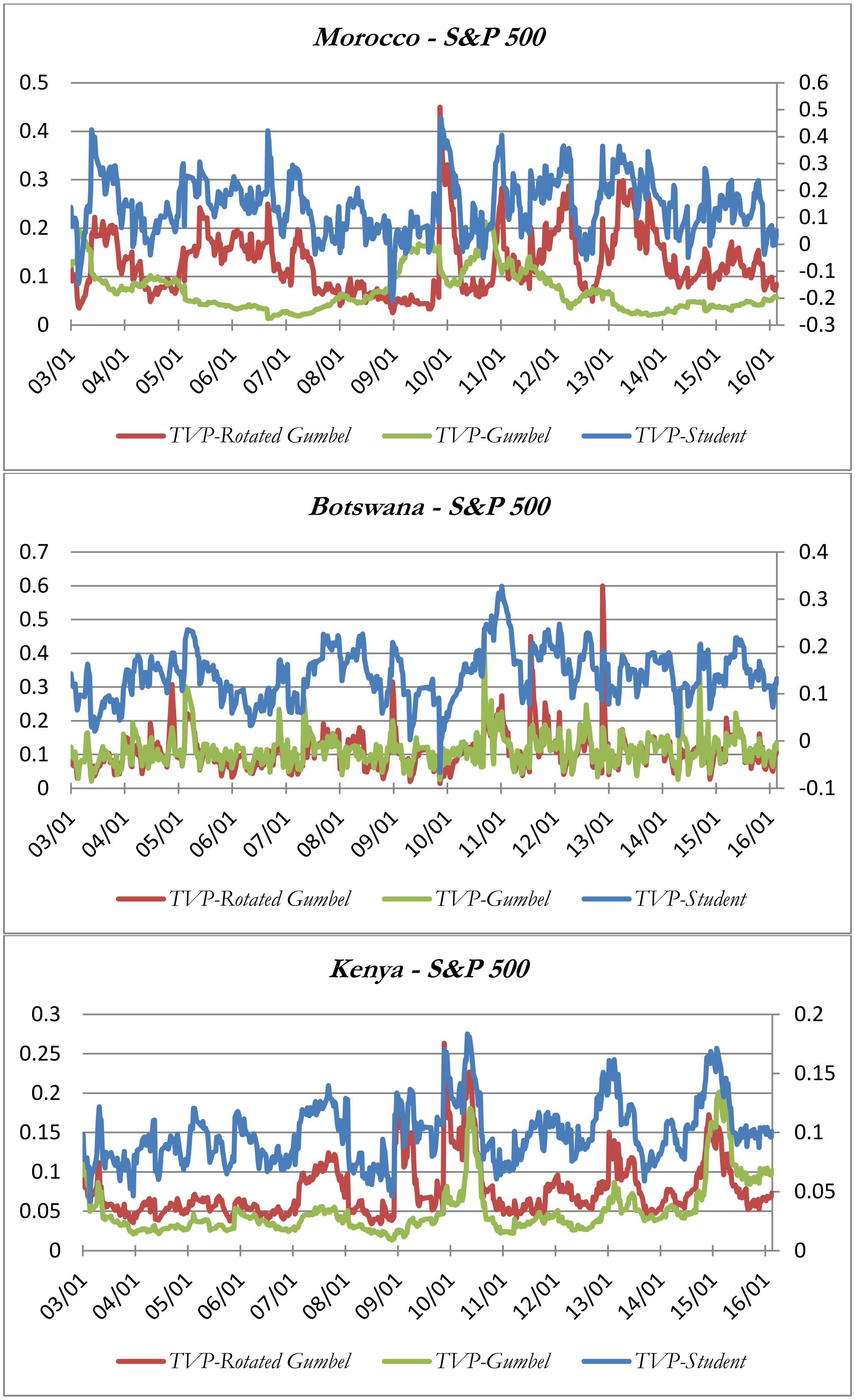


Figure 5.3: Time paths for time-varying dependence parameters between African and developed stock markets returns.

5.3.4 Toda Yamamotto (T-Y) model test results for interdependence

We examine the direction of flow between each of the foreign exchange rate and developed equity markets, on one hand, and each stock market in Africa, on the other hand using the T-Y causality test. Principally, we find out whether or not the nexus between the two asset markets is driven by the portfolio balance theory or flow-oriented model. The causality test results are shown in Table 5.12. Panels A-F show the causality between African stock markets returns and returns of USD exchange rate, EUR exchange rate, S&P 500, Asia ex-J, FTSE100, and EUSTXX, respectively. For all the causality tests, we specify a generally non-serially correlated optimal lag length using the Alkaike information criterion and the final predictor error statistics. Further, stability of the estimated VAR equations (for the T-Y causality tests) is checked using the inverse roots in column 7 of Table 5.12 and CUSUM plots. Since the inverses of the VAR roots are greater than 1 (*i.e.* q_1 and q_2 > 1), it implies the system passes the stability test. Similarly, the CUSUM plots also confirm stability at 5% significance level (though unreported due to space but available upon request). The above results suggest that the VAR system has been correctly specified.

In Panel A, the following observations are made: a unidirectional causality running from each of Egypt and Nigeria to the USD exchange rate, and a unidirectional causality running from the USD rate to each of Botswana and Kenya. For Panel B, bidirectional causality between the EUR and Botswana market is observed, in addition to a unidirectional causality from Morocco to the EUR exchange rate. Thus, we find evidence in support of the portfolio balance theory (causality from stocks to exchange rates) and flow-oriented model (causality from exchange rates to stocks), as well, as markets interdependence (bidirectional causality). Except for the case of South Africa that shows strong independence with each of the USD and EUR exchange rates, the other results are not entirely unexpected. Plausibly, South Africa, unlike the other markets shows such independence due to the relatively less existence of 'de-facto' dollarization in its economy, despite the large flows of international portfolio capital into the country and higher transactional uses of the dollar compared to other currencies. It must be noted that, South Africa has the tightest capital control laws and measures in the sub-Saharan African sub-region in our sample. The differences in results may reflect the relative size, liquidity and degree of foreign investors' participation in each of the markets within the sample. Though, all countries sampled are opened to foreign investor participation, their capital markets have differing degrees of openness.

Table 5.12: Toda-Yamamoto causality test results and diagnostics

Panel A

	African stock does not Granger cause USD rate		USD rate does not Granger cause African stock		Diagnostics	
	χ^2	*lags*	χ^2	*lags*	*B-G LM test*	*VAR roots*
Botswana	25.0	15	44.7*	15	31.05	$q_{1,2} > 1$
Egypt	17.6*	3	2.1	3	39.05*	$q_{1,2} > 1$
Kenya	3.2	2	7.2**	2	29.69	$q_{1,2} > 1$
Morocco	14.1	9	8.3	9	28.69	$q_{1,2} > 1$
Nigeria	33.5*	6	4.3	6	37.15**	$q_{1,2} > 1$
South Africa	2.7	2	4.0	2	39.72*	$q_{1,2} > 1$

Panel B

	African stock does not Granger cause EUR rate		EUR rate does not Granger cause African stock		Diagnostics	
	χ^2	*lags*	χ^2	*lags*	*B-G LM test*	*VAR roots*
Botswana	12.7*	3	8.0**	3	38.14*	$q_{1,2} > 1$
Egypt	6.2	3	3.7	3	28.52	$q_{1,2} > 1$
Kenya	11.4	9	10.2	9	28.68	$q_{1,2} > 1$
Morocco	8.2**	2	2.3	2	35.99**	$q_{1,2} > 1$
Nigeria	4.9	2	5.3	2	41.98*	$q_{1,2} > 1$
South Africa	0.14	2	1.7	2	34.24**	$q_{1,2} > 1$

Panel C

	African stock does not Granger cause S&P 500 returns		S&P 500 returns does not Granger cause African stock		Diagnostics	
	χ^2	*lags*	χ^2	*lags*	*B-G LM test*	*VAR roots*
Botswana	17.0**	9	25.4*	9	43.69*	$q_{1,2} > 1$
Egypt	56.9*	11	7.0	3	29.63	$q_{1,2} > 1$
Kenya	7.3	5	65.5*	5	28.46	$q_{1,2} > 1$
Morocco	46.2*	15	26.9**	15	33.33	$q_{1,2} > 1$
Nigeria	19.2**	10	38.3*	10	33.63**	$q_{1,2} > 1$
South Africa	0.07	2	2.9	2	39.02*	$q_{1,2} > 1$

Panel D

	African stock does not Granger cause Asia ex-J returns		Asia ex-J returns does not Granger cause African stock		Diagnostics	
	χ^2	*lags*	χ^2	*lags*	*B-G LM test*	*VAR roots*
Botswana	14.5	17	59.6*	17	28.82	$q_{1,2} > 1$
Egypt	52.8*	6	13.3**	6	38.19*	$q_{1,2} > 1$
Kenya	3.3	5	56.2*	5	32.66**	$q_{1,2} > 1$
Morocco	25.6	16	30.6**	16	33.48**	$q_{1,2} > 1$
Nigeria	1.3	3	59.0*	3	35.71**	$q_{1,2} > 1$
South Africa	7.0	2	2.7	2	52.46*	$q_{1,2} > 1$

Panel E

	African stock does not Granger cause FTSE 100 returns		FTSE 100 returns does not Granger cause African stock		Diagnostics	
	χ^2	*lags*	χ^2	*lags*	*B-G LM test*	*VAR roots*
Botswana	19.4	17	148.9	17	39.94*	$q_{1,2} > 1$
Egypt	64.2*	6	19.0*	6	30.27	$q_{1,2} > 1$
Kenya	5.3	4	47.1*	4	29.18	$q_{1,2} > 1$
Morocco	42.0*	16	29.2**	15	33.40**	$q_{1,2} > 1$
Nigeria	20.4**	9	69.6*	9	38.37*	$q_{1,2} > 1$
South Africa	0.58	2	2.2	2	31.34	$q_{1,2} > 1$

Panel F

	African stock does not Granger cause EUSTXX returns		EUSTXX returns does not Granger cause African stock		Diagnostics	
	χ^2	*lags*	χ^2	*lags*	*B-G LM test*	*VAR roots*
Botswana	0.86	3	3.6	3	29.07	$q_{1,2} > 1$
Egypt	16.8	12	12.8	12	31.28	$q_{1,2} > 1$
Kenya	9.2	10	8.1	10	28.64	$q_{1,2} > 1$
Morocco	10.1	8	5.2	8	29.01	$q_{1,2} > 1$
Nigeria	2.3	2	0.77	2	34.92**	$q_{1,2} > 1$
South Africa	13.8	13	17.0	13	32.8**	$q_{1,2} > 1$

*Notes: *, **, respectively represent 1%, and 5% significance levels. B-G denotes the Breusch-Godfrey LM statistics for serial correlation; $q_{1,2}$ denotes the inverse of the two roots from the VAR equations indicating parameter stability of the chi-square $\left[\chi^2\right]$ distributions of the Toda-Yamamoto causality tests.*

The World Economic Forum (2009) ranks Kenya as having the most accessible market with a score of 4.59 out of 10. It is followed by Morocco (4.09), Ghana (3.94), South Africa (3.78), Egypt (3.05), and Nigeria (2.72)[71] – see also, Kodongo and Ojah (2011). If foreign investors' market accessibility is a prerequisite to equity market's interdependence with the foreign exchange market, then it is not surprising that South Africa is not identified as the most linked market to foreign exchange markets. A natural observation from this result is that there could be other country-specific factors such as level of trade balances and bilateral economic ties with the European Union and United States of America, as well as, access to American Depository Receipts (ADRs) and country funds. Evidence in support of the flow-oriented model observed for Kenya may be explained by the following. Firstly, Kenya has the most accessible financial markets in Africa (as noted above), making the interaction between foreign exchange market and its stock market possible. Secondly, the industry mix of market indices in Kenya have heavy weightings in consumer goods, thus stock prices have more potential to be influenced by changes in trade balances, more than other factors.

In all, evidence of the portfolio balance theory for Egypt, Nigeria, and Morocco shows the relative verve of those markets to influence the stability of their local currencies. The results corroborate Kaminsky and Reinhart (1999) and Boako *et al.,* (2016) that a slowed economic activity leads to a fall in stock prices, and this influences international equity investors to withdraw their funds, thereby exerting a downward pressure on the domestic currency. Governments can therefore stimulate economic growth and equity markets in an attempt to avoid currency crisis.

From Panels C – F, causality among African stock and developed markets are shown. In all, the following pairs of causality relationships are observed. The S&P 500 shows a bi-directional causality with each of the market returns in Botswana, Morocco, and Nigeria. Additionally, whiles a unidirectional causality runs from Egypt to S&P500, causality runs from S&P500 to Kenya. For Asia ex-J, unidirectional causality runs from the developed market to each of the following markets in Africa – Botswana, Kenya, Morocco, and Nigeria. In the case of Egypt, however, causality is bidirectional. We observe bidirectional causality between the FTSE100 and each of the markets in Egypt, Morocco, and Nigeria; with a unidirectional causality running from FTSE100 to Kenya. No causality is found between the EUSTXX and any of the African markets. The above results indicate that most of the sampled markets in Africa have higher interdependences with corresponding

[71] Botswana is not covered by the study.

Table 5.13: Descriptive statistics and tests for downside value-at-risk (VaR) and conditional value-at-risk (CoVaR) for African stock returns

	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR < VaR$	VaR	CoVaR	$H_0: CoVaR = VaR$ $H_1: CoVaR < VaR$
	EUR exchange rate returns			***USD exchange rate returns***		
Botswana	-37.842	-15.319	0.077	-37.842	-13.762	0.081
	[5.309]	[78.483]	(0.412)	[5.309]	[65.112]	(0.320)
Egypt	-73.247	-16.190	0.000	-73.247	-16.252	0.000
	[19.751]	[2.167]	(1.000)	[19.751]	[2.206]	(1.000)
Kenya	-53.671	-16.557	0.096	-53.671	-15.650	0.099
	[23.383]	[2.872]	(0.218)	[23.383]	[1.921]	(0.107)
Morocco	-40.274	-10.564	0.099	-40.274	-9.482	0.000
	[12.108]	[1.157]	(0.197)	[12.108]	[0.379]	(1.000)
Nigeria	-63.462	-24.694	0.039	-63.462	-25.176	0.075
	[28.323]	[3.076]	(0.944)	[28.323]	[3.553]	(0.560)
South Africa	-67.699	-17.435	0.000	-67.699	-16.386	0.087
	[26.009]	[0.723]	(1.000)	[26.009]	[0.336]	(0.309)
	ASIAJ-ex.J stock returns			***FTSE100 stock returns***		
Botswana	-37.842	-19.581	0.023	-37.842	-20.699	0.063
	[5.309]	[115.082]	(0.964)	[5.309]	[124.691]	(0.499)
Egypt	-73.247	-16.584	0.020	-73.247	-16.459	0.006
	[19.751]	[2.451]	(0.967)	[19.751]	[2.359]	(0.989)
Kenya	-53.671	-16.627	0.034	-53.671	-16.626	0.081
	[23.383]	[2.945]	(0.958)	[23.383]	[2.944]	(0.342)
Morocco	-40.274	-10.428	0.015	-40.274	-10.414	0.034
	[12.108]	[1.059]	(0.987)	[12.108]	[1.049]	(0.943)
Nigeria	-63.462	-25.393	0.043	-63.462	-25.360	0.023
	[28.323]	[3.772]	(0.851)	[28.323]	[3.739]	(0.963)
South Africa	-67.699	-20.967	0.071	-67.699	-21.016	0.045
	[26.009]	[4.287]	(0.472)	[26.009]	[4.337]	(0.871)
	EUXTX stock returns			***S&P500 stock returns***		
Botswana	-37.842	-19.974	0.065	-37.842	-19.739	0.065
	[5.309]	[118.456]	(0.518)	[5.309]	[116.441]	(0.508)
Egypt	-73.247	-16.345	0.021	-73.247	-16.594	0.091
	[19.751]	[2.275]	(0.968)	[19.751]	[2.459]	(0.233)
Kenya	-53.671	-16.629	0.018	-53.671	-16.563	0.079
	[23.383]	[2.947]	(0.982)	[23.383]	[2.878]	(0.552)
Morocco	-40.274	-10.466	0.042	-40.274	-10.349	0.007
	[12.108]	[1.086]	(0.853)	[12.108]	[1.002]	(0.994)
Nigeria	-63.462	-25.254	0.045	-63.462	-25.095	0.034
	[28.323]	[3.634]	(0.849)	[28.323]	[3.476]	(0.879)
South Africa	-67.699	-20.966	0.067	-67.699	-20.901	0.056
	[26.009]	[4.287]	(0.511)	[26.009]	[4.221]	(0.879)

Notes: Standard deviations (%) for CoVaR and VaR are in squared brackets. P-values for the K-S statistic are in brackets.

developed markets. Evidence of large interdependences is found for the local markets and the FTSE100 and S&P500. The markets in Asia rather have higher influential effects on the Africa stocks than can the latter have on the former. It appears difficult to ascribe the above established causality phenomena to levels of market integration of African stocks, as the most integrated market

– South Africa fails to exhibit signs of any causal relationship with any of the developed markets. Intuitively, we can surmise that because the industry mix in market indices is different from country to country, it could be that the similarities or differences in sector weightings are influencing the relationship more than market integration or co-movements. Whilst markets such as Egypt, South Africa, Morocco, S&P 500, and FTSE 100 have heavy weightings towards the financial sector, some African markets, such as Kenya, have heavy weightings in consumer goods, like food and beverages. The emerging markets in Asia are heavily weighted towards manufacturing, communications and utilities. Thus, the possibility that markets with similar sectoral composition and therefore a similar cyclical relationship with global and local fundamentals will have greater links and be unitary or mutually causal cannot be overlooked.

5.3.5 Exchange rates and developed markets spillover effects to African stock returns

Following the two-step procedures already described in the methodology, we apply the best fit copula approach for each time period to examine spillover effects. At each period, the CoVaR value for African stock returns is obtained at the 95% confidence level $(\beta = 0.05)$ conditional on the VaR value for the foreign exchange rate and developed stock returns at the 95% confidence level $(\alpha = 0.05)$. The results for the temporal dynamics for the downside (bear market) VaR and CoVaR values for stock returns considering spillovers from exchange rates and developed stock markets are shown in Panels A-E of Figure 5.4, whilst the descriptive statistics and hypothesis test (based on Kolmogorov-Smirnov statistics, Equation. 5.5.7) test results are shown in Table 5.13.

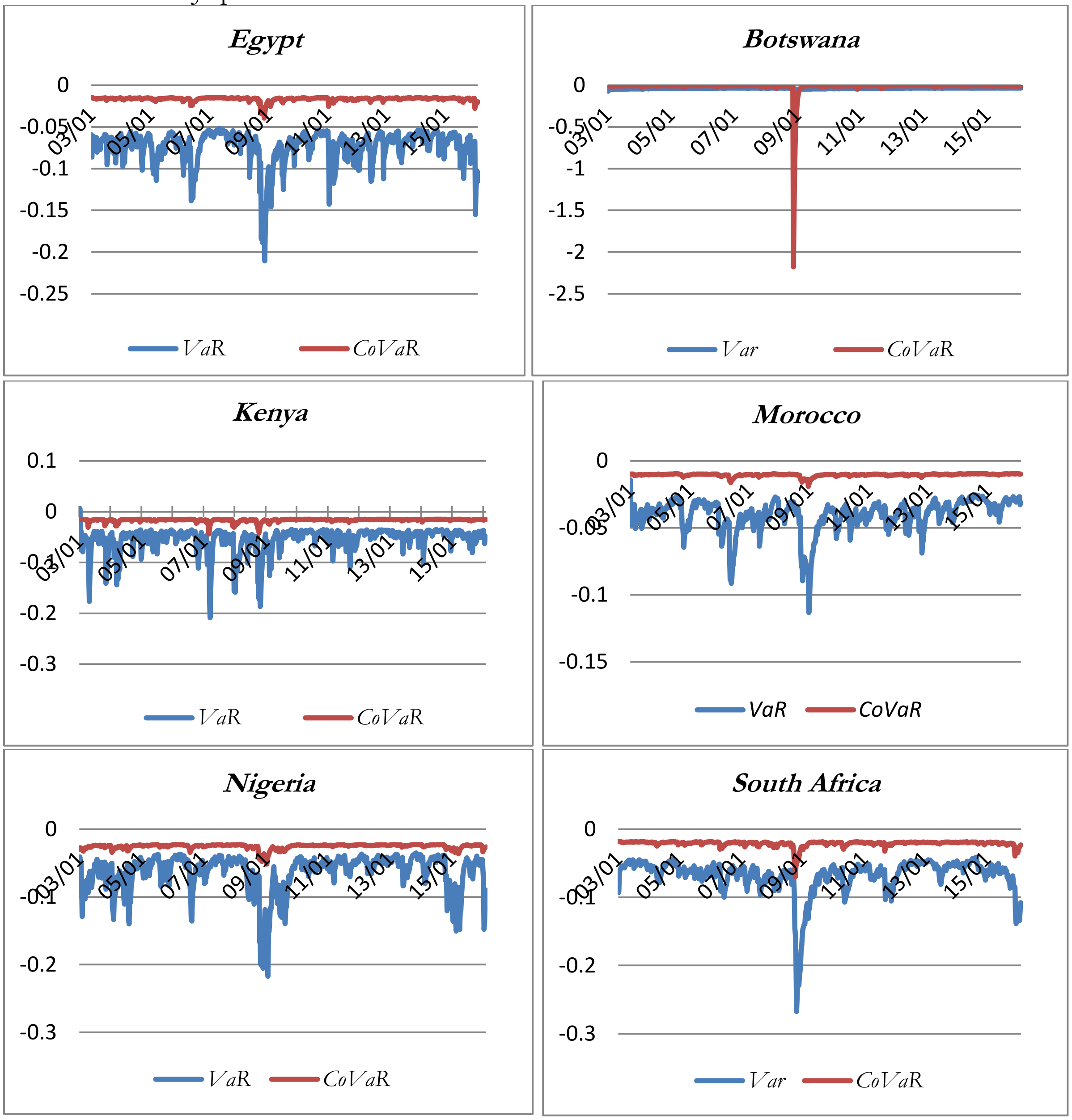
We observe from the plots that the VaR and CoVaR values show marked similarities in trends for all countries, albeit differences in magnitude across countries. Abrupt changes in the time path of the graphs are mostly noticed around 2007-2008 and 2009-2010 corresponding to the periods of the global financial crises and Eurozone debt crises, respectively. Across all countries and markets, CoVaR values are identified to be systematically above VaR values (i.e. CoVaR values were less negative than VaR values). This graphical evidence is supported by the non-significance of the Kolmogorov-Smirnov (K-S) bootstrapping test (see Equation 5.5.7) depicted in Table 5.13. For downside spillovers, such a feature suggests the unavailability of spillover effects. Thus, extreme downwards changes in exchange rates (depreciation of the local currency against the USD or EUR) and bear market conditions in developed equity markets could not lead to shock transmission to

African stock markets. The lack of spillover effects for the full sample data may be due to the fact that in the full sample, the peculiarity of the data can be masked, since it reflects an aggregation of periodic characteristics of the entire sample. Perhaps, a sub-sample analysis may capture specific market shocks or innovations. We consider this in the next sub-section.

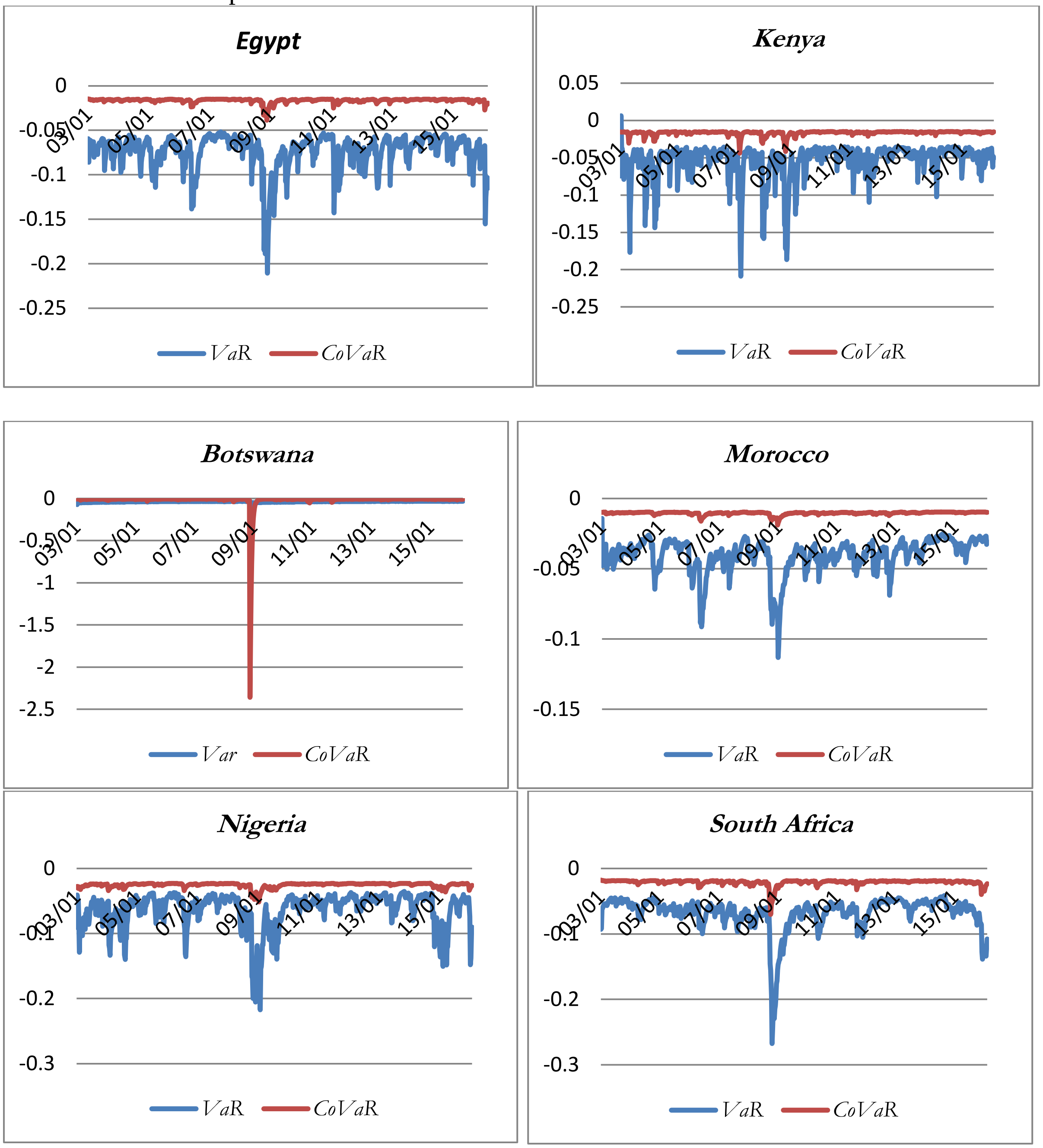
In the case of no adverse spillover effects from exchange rates, a plausible inference is that extreme (depreciation) of the local currency against the EUR or USD makes local currency denominated assets in domestic stock markets cheaper. This may attract international investors into the local markets. As more funds flow to the local market through purchases of securities, stock prices will ultimately respond to the increases in expected cash flows. This result is at variance with Reberodo *et al.,* (2016) which find spillover effects from the EUR and USD exchange rates to emerging markets. The authors attribute the exchange rate spillover effects to 'flight-to-quality' of foreign investors. Our results, to some extent corroborate that of Kodongo and Ojah (2011) suggesting that international portfolio investors can seek diversification into African equity markets without worrying about unconditional risks associated with foreign exchange rate fluctuations.

The lack of spillover effects from developed equity markets to African stocks is not entirely unexpected on account of the relative size, liquidity, and degree of foreign investors' participation in each of the local markets in the sample. Daryl and Biekpe (2002) make similar observation. Apart from the small sizes and low-liquidity levels, most of the markets in Africa are relatively nascent and also less accessible to foreign investors, partly due to the absence of ADRs. Thus, if foreign investor participation is a pre-requisite to spillover effects, it would be very surprising to observe spillover effects from any of the developed markets to the African stock markets – see also Daryl and Biekpe (2002). Perhaps, there may be spillovers from economies of the developed markets to African stock markets through other channels (example, the real sectors of the economies) and not necessarily, through stocks. This calls for further studies exploring the possible channels of international spillover effects (beyond the scope of this study).

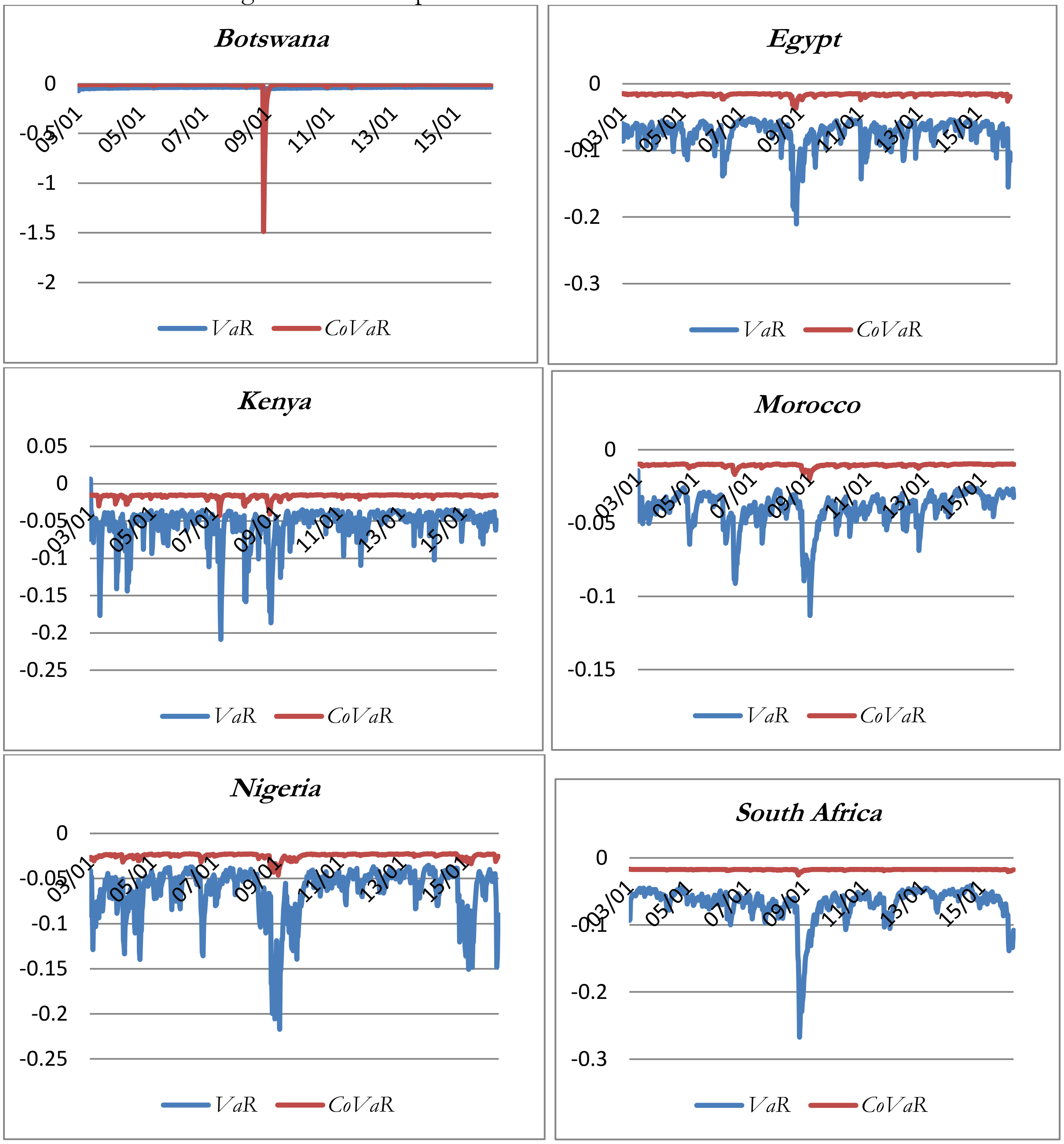
Panel A: Asia-ex.J spillover effects to African stocks



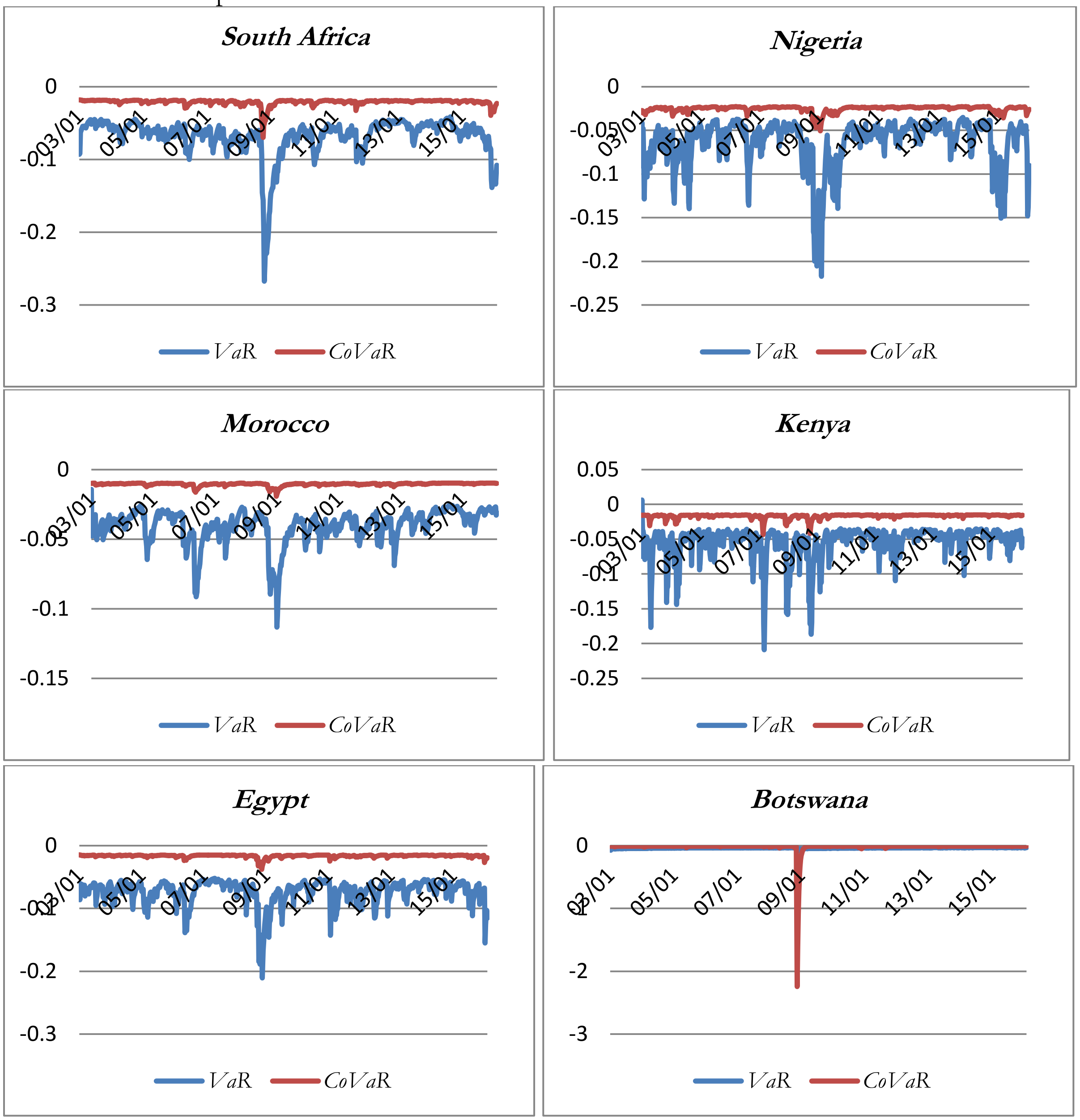
Panel B: FTSE100 spillover effects to African stocks



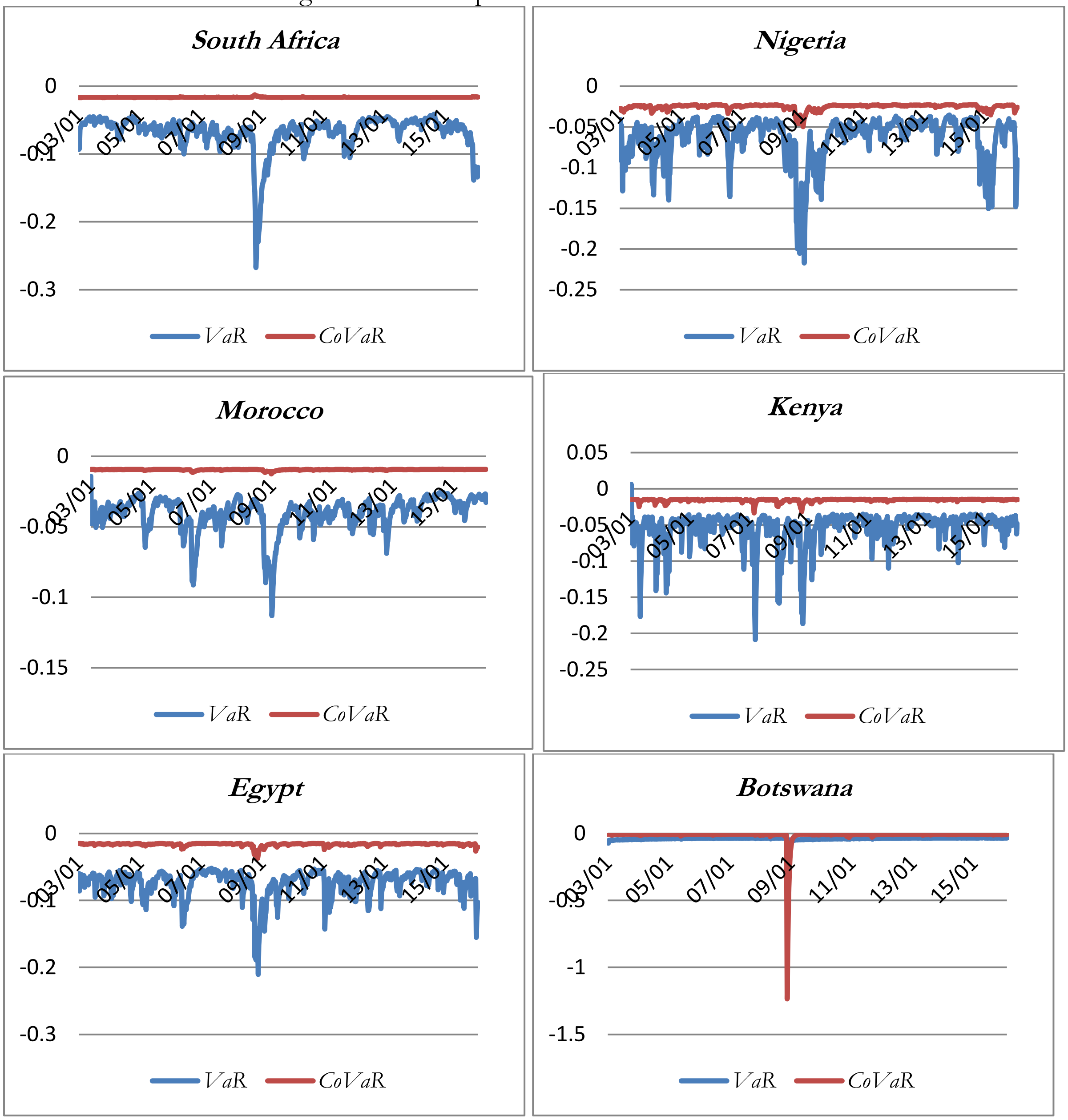
Panel C: EUR exchange rate returns spillover effects to African stocks



Panel D: EUSTX spillover effects to African stocks



Panel E: US Dollar exchange rate returns spillover effects to African stocks



Panel F: S&P500 spillover effects to African stocks

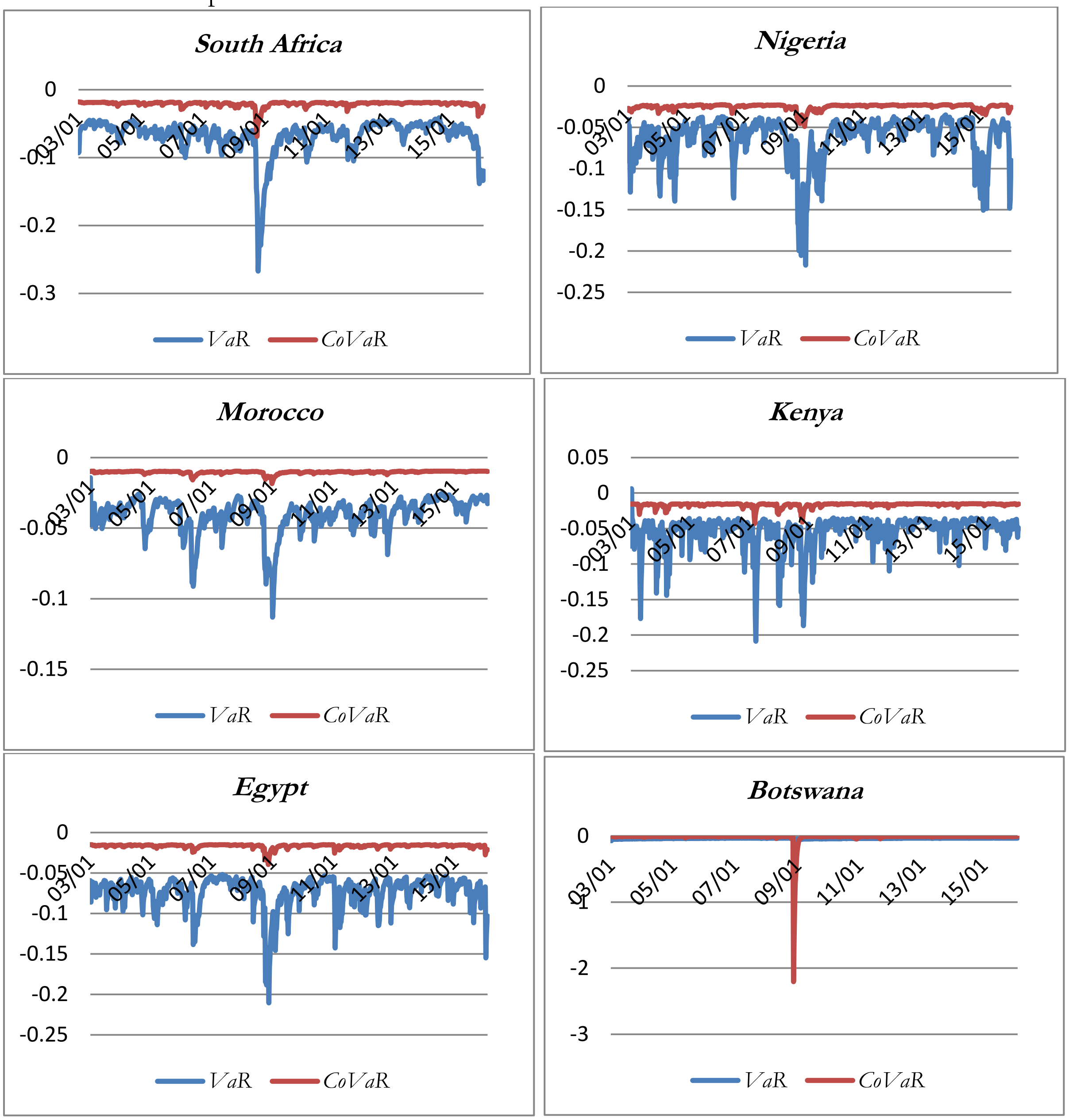


Figure 5.4: Downside value-at-risk (VaR) and conditional value-at-risk (CoVaR) for African stock market returns.

5.3.6 Is there evidence of 'shift-contagion' in African stock markets?

It is instructive to note that the "shift-contagion" theory obviously considers positive changes in the cross-market correlations only during the life-span of crisis. This view suggests that transmission of shocks can occur only when crisis are known to be in existence. Meanwhile, the transmission mechanism of shocks may not always be direct, and that, intercepted shocks or shocks that pass through longer channels may be transmitted to target markets or countries even when the crisis is considered dead or eased. This holds more seriously for emerging/developing and/or markets that are not highly integrated, and therefore do not share similar cyclical relationship with global markets (or origins of shocks), making them naturally insulated or decoupled from immediate spillovers from crisis. For this reason, we argue that most emerging/developing markets may generally be decoupled from initial spillovers of shocks during crisis and that examining the occurrence of contagion based on the "shift-contagion" theory may usually lead to the conclusion of "no contagion". This stands to diffuse the widely held opinion that '*when the US [developed economies] sneeze, all other economies catch a cold'*. In contrast, the truism is that the speed and intensity of such infectious spread may be higher in countries with higher proximity to the '*flu-infected*' economy (e.g. USA) than those that are distance apart. In view of the above, we propose to extend the "shift-contagion" theory and postulate a **"delayed shift-contagion"** theory – *thus, increases in cross-market linkages/spillovers during crises.*

Two key reasons account for the distinction between "shift-contagion" and "delayed shift-contagion". First, focusing on only crisis periods to establish contagion may be misleading on the grounds that contagion may occur because shocks are in excess due to the crisis or by mere coincidence. Thus, if shocks were not in excess, contagion may not occur through any channel. Secondly, in the crisis period, every economic agent is equally exposed to the shock and so it becomes really difficult to trace the channel of transmission. However, in the immediate post-crisis era and even beyond, it would take really critical factors such as market integration, similarities in cyclical relationships and sector compositions of indices, trade relations, cross-border listings, interactive effects of macro-economic factors, etc., or other forms of significant connectivity for contagion to occur. Third, the reliance on increased correlation during crisis to denote contagion may be misleading since correlation will expectedly be high during periods of market volatility – see also Bekaert *et al.,* (2005). It is our considered opinion that policy makers and practitioners would be keen in finding out whether contagion from global shocks, if any, to particularly, emerging financial markets are as a result of excessive shocks or market and economic specific linkages; or whether such shock transmissions occur after the crisis has eased. A more compelling reason to explore avenues for the establishment of the shift-contagion theory in respect of shock transmission after a crisis is the suggestion by extant literature that shocks, particularly from the U.S exert significant influence on other economies during tranquil periods (Dungey and Gujurel, 2015).

To carry-out the test for shift- and/or delayed shift-contagion, we disaggregate the full sample data into sub-samples, taking into account the 2007-2009 global financial crises. The choice of this crisis period is because it is arguably the major global financial crisis after the Great Depression between 1929 and 1932. A great deal of uncertainty surrounds when the GFC actually started and ended. However, for the purpose of this chapter, we use the crisis period suggested by Dungey and Gajurel (2015). Thus, we choose a crisis start date of August 9, 2007[72]; a period corresponding with the beginning of European Central Bank's (ECB) intervention in the market and the seizure in the banking system by BNP Paribas intimating the halt of activities in three funds with specialty in U.S mortgage debt. With this, the considered crises end point is May, 8, 2009, consistent with end of the recession in the US. Thus, the disaggregated data comprise a). a pre-crises period from January, 10, 2003 to August, 7, 2007; b). a crises period from August, 9, 2007 to May, 5, 2009; and c) a post-crises period from May, 8, 2009 to February, 12, 2016. The suggestion by Claessens *et al.,* (2010), Mishkin (2011), and Dungey and Gajurel (2015) are in favour of splitting the crisis into phases: the turmoil phase (from August 2007 to mid-September 2008, until the demise of Lehman Brothers) and the acute phase (after the collapse of Lehman Brothers until May 2009). Phase I (the turmoil phase) captures the sub-prime crises and its effects on financial markets globally. For example, August 2007 marks the seizure in the banking system by BNP Paribas intimating the halt of activities in three funds with specialty in U.S mortgage debt. The period saw a credit freeze in interbank markets, central banks provision of substantial liquidity support to banks, and the action of governments to rescue financial institutions such as ABN Amro in the Netherlands, Northern Rock in the UK, and Bear Stearns in the US – see also Dungey and Gajurel (2015). Phase II (the acute stage) marks the bankruptcy of Lehman Brothers, when turmoil in the financial markets led to the failure of a large number of financial institutions globally, with various governments interventions, especially the G20's cutting of interest rates, provision of various fiscal stimuli and bail-out packages, and pursuing quantitative easing policies in an attempt to avoid the recession becoming a slump.

To incorporate the aggregation of the sub-samples for examining contagion/spillover effects, we apply the K-S two-step statistical test (see equation 5.5.7) to examine whether or not the conditional distribution function (CDF) of the mean conditional value-at-risk (CoVaR) of two succeeding sub-samples are significantly different. For instance, we test whether or not the expected value of CoVaR

[72] Larry Elliot, the Economist editor, in the 7th August, 2011 edition of the Guardian also affirms same start date.

for pre-crisis period is significantly different from that of Phase I; if that of Phase II is significantly different from that of Phase I; and lastly, if that of the post-crises period is significantly different from that of Phase II. For this, we repeat equation 5.5.7 as:

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} \sup_{x} | F_m(x) - G_n(x) | \qquad [5.5.8]$$

where $F_m(x)$ and $G_n(x)$ respectively, denote the cumulative expected conditional value-at-risk (CoVaR) quantile distribution functions for two successive periods (e.g. pre-crisis and Phase I), in that order; and *n* and *m* denote the size of the two samples. Thus, we test the hypothesis of equality between the expected CoVaR of domestic stock market return quantiles (for different successive sub-sample), as follows

$$H_0 : CoVaR_q = CoVaR_j$$

$$H_1 : CoVaR_q < CoVaR_j$$

where, *j* and *q* are respectively, preceding and successive periods.

It must be emphasized that the hypothesis testing used in our study differs from Forbes and Rigobon (2002). Their test statistic to determine contagion was calculated using estimated sample variances. However, Corsetti *et al.,* (2005) and latter Daryl and Biekpe (2002) suggest that the Forbes and Rigobon (2002) approach has arbitrary and unrealistic restrictions on the variance of country-specific shocks. Corsetti *et al.,* (2005) believes that a change in variance might be driven by an increase in the variance of a common factor, which then causes a higher than usual volatility in other markets. Testing for contagion, therefore, does not need to be conditional on observing a rise in correlation, as contagion is likely to be defined as co-movements which are too strong relative to what can be expected from an unchanged transmission mechanism (Daryl and Biekpe, 2002). The KS-test has the advantage of overcoming the restrictive test by Forbes and Roigobon (2002) since the former makes no assumption about the distribution of data. The above motivate why we do not use the Forbes and Rigobon (2002) test statistic measure and correlation to estimate contagion.

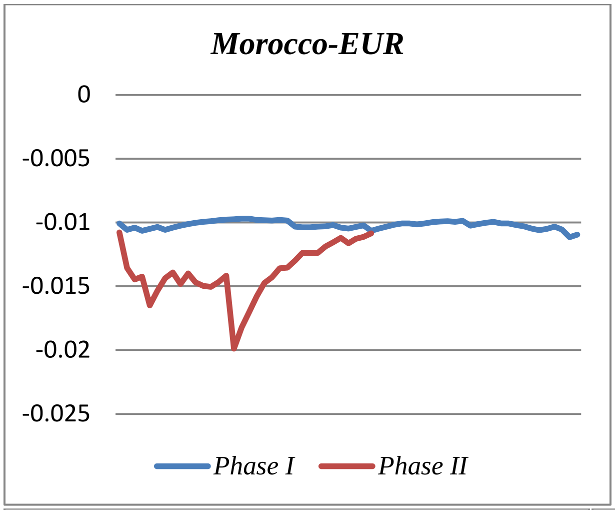
Similar to *Section 5.3.5*, we apply the best-fit (optimal) copula approach for each time period to examine spillover effects. Table 5.14 summarizes the results of best-fit (optimal) copulas and the best copula model when forcing the parameter of dependence to remain constant for each market pair (e.g. Kenya-EUR, Nigeria-FTSE100, etc.).

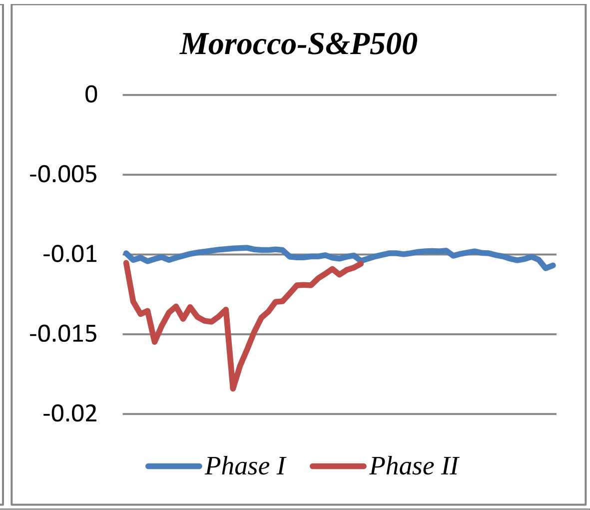
Table 5.14: Best-fit (optimal) copula selection – full sample

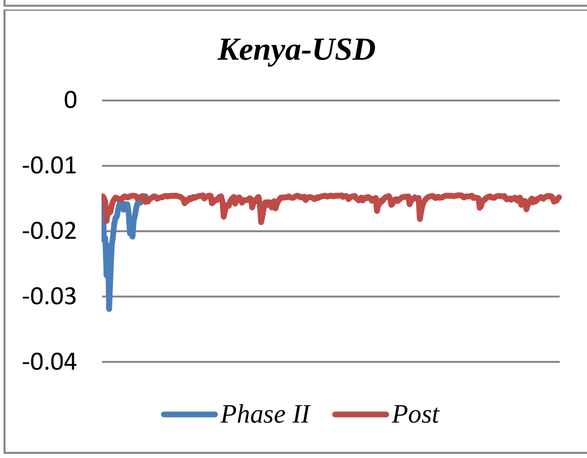
	Copula selected		Copula selected	
	Constant	***Time-varying***	***Constant***	***Time-varying***
	Panel A: USD and African market pairs		***Panel B: EUR and African market pairs***	
Kenya	Gaussian			TV-Student-t
South Africa		TV- rotated Gumbel		TV-Student-t
Egypt		TV-Gaussian		TV-Gaussian
Nigeria		TV-Student-t	Rotated Gumbel	
Morocco	Student-t		Rotated Gumbel	
Botswana		TV-Student-t		TV-Gaussian
	Panel C: Asia ex-J and African market pairs		***Panel D: EUXTX and African market pairs***	
Kenya		TV- rotated Gumbel	Rotated Gumbel	
South Africa	Student-t			TV-Student-t
Egypt		TV-Gaussian	Gaussian	
Nigeria	Student-t			TV-rotated Gumbel
Morocco		TV- rotated Gumbel		TV- rotated Gumbel
Botswana		TV-Gaussian		TV-Gaussian
	Panel E: FTSE100 and African market pairs		***Panel F: S&P500 and African market pairs***	
Kenya	Rotated Gumbel		Rotated Gumbel	
South Africa	Student-t			TV-Student-t
Egypt	Gaussian			TV-Gaussian
Nigeria	Student-t		Gumbel	
Morocco		TV-Gaussian	Rotated Gumbel	
Botswana		TV-Gaussian	Gaussian	

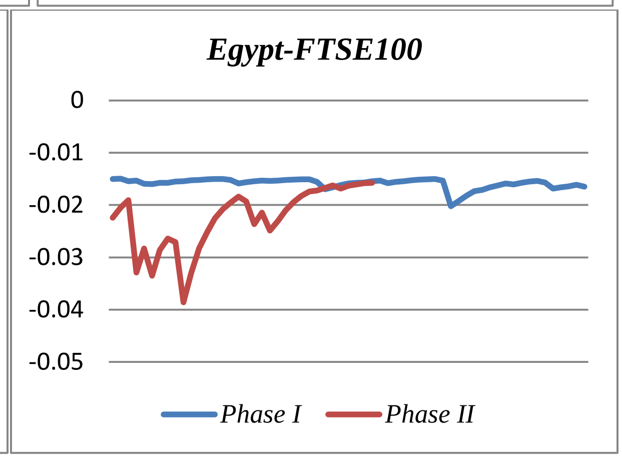
TV denotes time-varying. Optimal Copulas are selected based on the AIC.

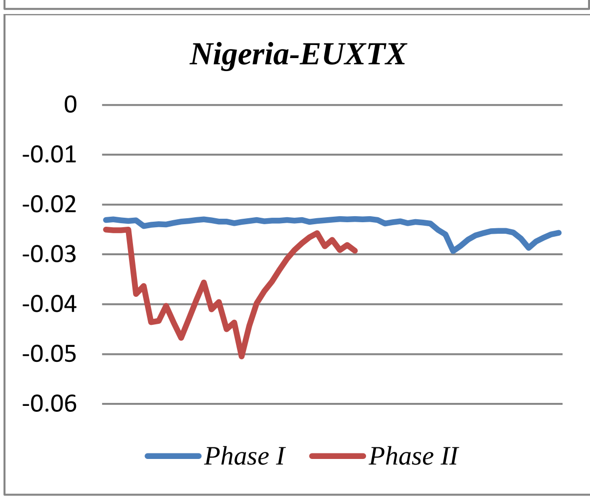
Table 5.15 shows the summary statistics and hypothesis tests for the downside CoVaR values for African stock market returns (for pre-crisis/Phase I, Phase I/Phase II, and Phase II/post- crisis periods) by considering spillover effects from foreign exchange rates and developed equity markets. Graphical results of the temporal dynamics for the spillovers are reported only for situations where spillover (contagion) is identified – see Figure 5.5. The rest are available upon request due to conservation of space. The graphical results generally show evidence of similar trend in the CoVaR for the pre-crises and Phase I periods, though they varied at some specific periods. From Figure 5.5, we observe abrupt changes in the time path of the graphs mostly around the early stages of Phase II of the crisis. The changes correspond with the first quarter of 2009 where the G20 cut interest rates, various fiscal stimuli, and pursed quantitative easing policies in an attempt to avoid the recession becoming a slump. From the mean CoVaRs (%) in Table 5.15, it is observed that in most cases the

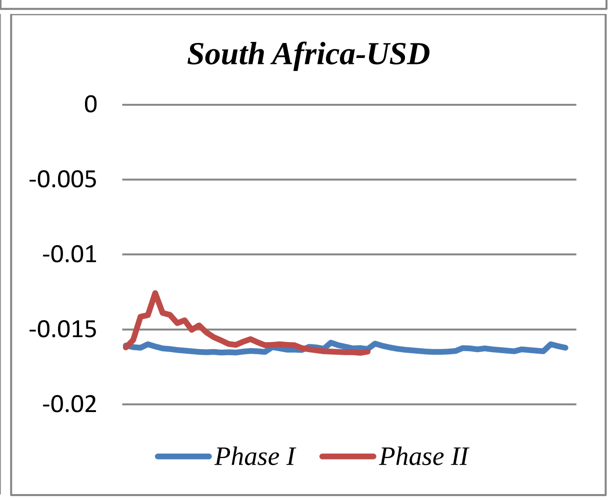

Morocco-EUR
0
-0.005
-0.01
-0.015
-0.02
-0.025
Phase I
Phase II


Morocco-S&P500
0
-0.005
-0.01
-0.015
-0.02
Phase I
Phase II


Kenya-USD
0
-0.01
-0.02
-0.03
-0.04
Phase II
Post


Egypt-FTSE100
0
-0.01
-0.02
-0.03
-0.04
-0.05
Phase I
Phase II


Nigeria-EUXTX
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
Phase I
Phase II


South Africa-USD
0
-0.005
-0.01
-0.015
-0.02
Phase I
Phase II

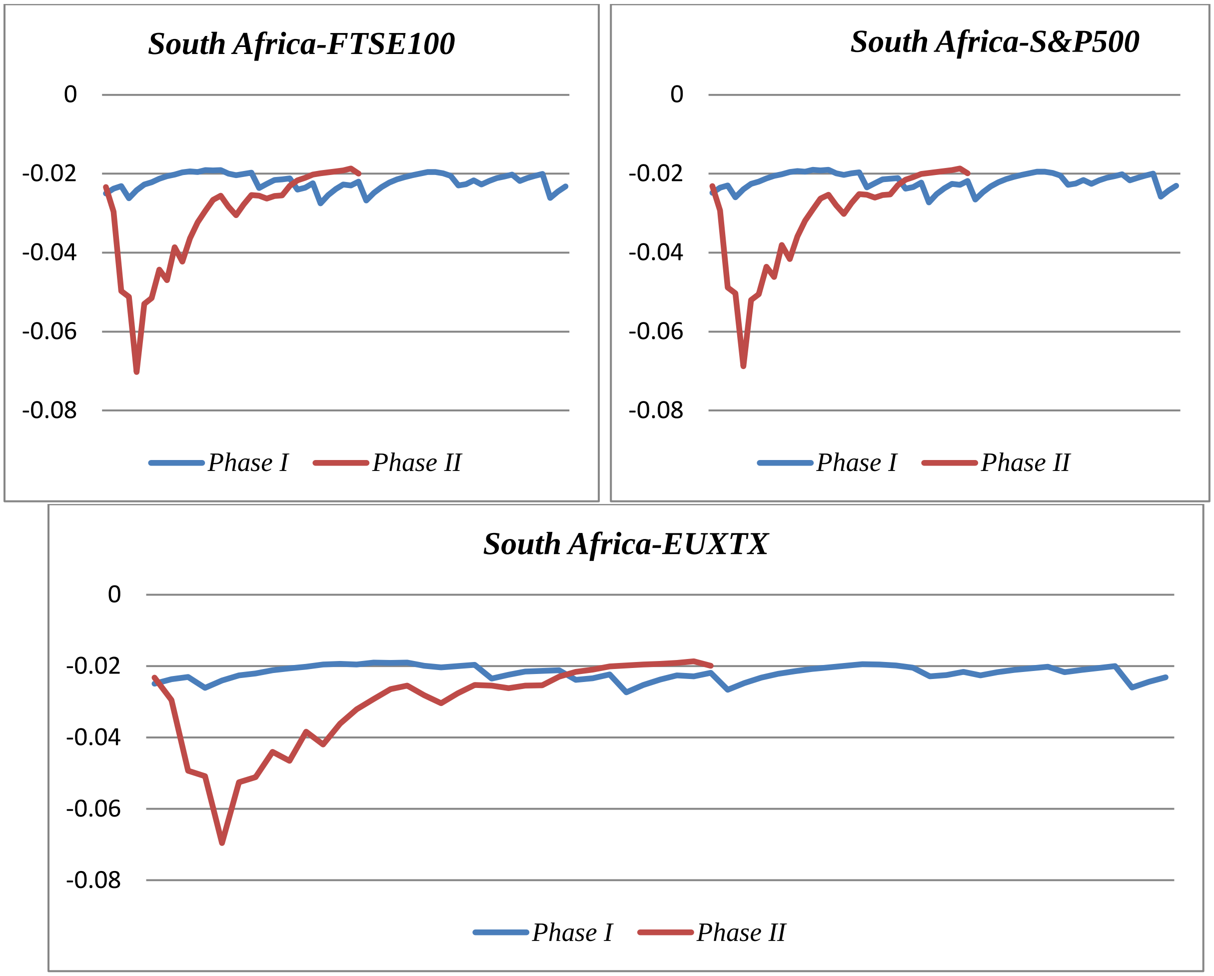


Figure 5.5: Downside conditional value-at-risk (CoVaR) for African stock market returns.

CoVaR for Phase I is less than that for the pre-crisis period signifying evidence of contagion. However, the K-S statistic suggests that there is no significant difference between the means of CoVaRs for the said periods, and hence contagion could not be said to have occurred. Evidence of contagion is established where mean CoVaR values are identified to be systematically more negative for a successive period (say, Phase II) than for a preceding period (say Phase I) and the corresponding Kolmogorov-Smirnov (K-S) bootstrapping test statistic is significant. Instances of contagion in Table 5.15 are highlighted in bold.

Table 5.15: Descriptive statistics and tests for shift-contagion in African stock returns using downside CoVaR

	$CoVaR_{[1]}$	$CoVaR_{[2]}$	H_0/H_1	$CoVaR_{[2]}$	$CoVaR_{[3]}$	H_0/H_1	$CoVaR_{[3]}$	$CoVaR_{[4]}$	H_0/H_1
Panel A: EUR exchange rate returns									
Botswana	-7.906	-9.438	0.020	-9.438	-14.863	0.000	-14.863	-8.431	0.025
	[1.838]	[3.568]	(0.964)	[3.568]	[0.324]	(1.000)	[0.324]	[3.354]	(0.956)
Egypt	-15.818	-15.653	0.099	-15.653	-21.740	0.000	-21.740	-16.013	0.045
	[1.212]	[0.887]	(0.284)	[0.887]	[5.381]	(1.000)	[5.381]	[1.433]	(0.834)
Kenya	-16.950	-17.721	0.013	-17.721	-20.697	0.059	-20.697	-15.694	0.093
	[3.290]	[3.287]	(0.984)	[3.287]	[5.863]	(0.560)	[5.863]	[0.906]	(0.214)
Morocco	-10.614	-10.202	0.086	-10.202	-13.893	**0.085**	-13.893	-10.272	0.000
	[1.052]	[0.304]	(0.392)	[0.304]	[2.078]	(0.000)	[2.078]	[0.492]	(1.000)
Nigeria	-24.509	-23.845	0.030	-23.845	-33.240	0.000	-33.240	-24.136	0.095
	[1.870]	[1.338]	(0.961)	[1.338]	[6.388]	(1.000)	[6.388]	[2.055]	(0.202)
South Africa	-17.258	-17.597	0.009	-17.597	-19.171	0.039	-19.171	-17.358	0.047
	[0.307]	[0.343]	(0.993)	[0.343]	[2.077]	(0.936)	[2.077]	[0.436]	(0.833)
Panel B: USD exchange rate returns									
Botswana	-7.612	-8.883	0.020	-8.883	-124.363	0.000	-124.363	-8.048	0.031
	[1.525]	[2.960]	(0.964)	[2.960]	[268.660]	(1.000)	[268.660]	[2.783]	(0.912)
Egypt	-15.864	-15.696	0.019	-15.696	-21.893	0.000	-21.893	-16.063	0.044
	[1.234]	[0.903]	(0.963)	[0.903]	[5.497]	(1.000)	[5.497]	[1.456]	(0.834)
Kenya	-15.912	-16.428	0.027	-16.428	-8.419	0.056	-8.419	-15.072	**0.693**
	[2.230]	[2.199]	(0.943)	[2.199]	[-3.922]	(0.559)	[-3.922]	[0.606]	(0.000)
Morocco	-9.498	-9.364	0.016	-9.364	-10.572	0.000	-10.572	-9.386	0.085
	[0.345]	[0.009]	(0.963)	[0.009]	[0.680]	(1.000)	[0.680]	[0.161]	(0.496)
Nigeria	-24.696	-24.174	0.000	-24.174	-35.045	0.000	-35.045	-24.528	0.095
	[2.161]	[1.540]	(1.000)	[1.540]	[7.379]	(1.000)	[7.379]	[2.374]	(0.292)
South Africa	-16.468	-16.310	0.053	-15.578	16.310	**0.595**	-15.578	-16.422	0.004
	[0.143]	[0.160]	(0.556)	[0.160]	[0.967]	(0.000)	[0.967]	[0.203]	(0.999)
Panel C: ASIAJ-ex.J stock returns									
Botswana	-8.711	-10.958	0.019	-10.958	-215.059	0.000	-215.059	-9.481	0.000
	[2.695]	[5.232]	(0.964)	[5.232]	[474.841]	(1.000)	[474.841]	[4.918]	(1.000)
Egypt	-16.153	-15.966	0.099	-15.966	-22.852	0.000	-22.852	-16.374	0.056
	[1.371]	[1.003]	(0.284)	[1.003]	[6.088]	(1.000)	[6.088]	[1.617]	(0.647)
Kenya	-17.030	-17.821	0.013	-17.821	-20.873	0.057	-20.873	-15.742	0.049
	[3.374]	[3.371]	(0.984)	[3.371]	[6.0133]	(0.534)	[6.0133]	[0.929]	(0.792)
Morocco	-10.713	-10.097	0.021	-10.097	-13.477	0.000	-13.477	-10.161	0.086
	[1.385]	[0.279]	(0.968)	[0.279]	[1.903]	(1.000)	[1.903]	[0.450]	(0.339)
Nigeria	-25.176	-24.332	0.011	-24.332	-35.873	0.000	-35.873	-25.692	0.023
	[2.294]	[1.635]	(0.973)	[1.635]	[7.834]	(1.000)	[7.834]	[4.606]	(0.919)
South Africa	-19.918	-21.929	0.007	-21.929	-31.268	0.024	-31.268	-20.507	0.018
	[1.824]	[2.034]	(0.988)	[2.034]	[12.322]	(0.979)	[12.322]	[2.585]	(0.945)
Panel D: FTSE100 stock returns									
Botswana	-8.922	-11.357	0.019	-11.357	-223.892	0.000	-223.892	-9.509	0.001
	[2.920]	[5.669]	(0.964)	[5.669]	[486.258]	(1.000)	[486.258]	[4.964]	(0.998)
Egypt	-16.087	-15.865]	0.015	-15.865]	-22.161	**0.467**	-22.161	-16.161	0.021
	[1.332]	[0.966]	(0.978)	[0.966]	[5.649]	(0.000)	[5.649]	[-1.486]	(0.856)
Kenya	-17.028	-17.818	0.013	-17.818	-20.869	0.059	-20.869	-15.743	0.074
	[3.372]	[3.369]	(0.974)	[3.369]	[6.010]	(0.560)	[6.010]	[0.930]	(0.461)
Morocco	-10.692	-10.480	0.031	-10.480	-13.433	0.000	-13.433	-10.192	0.071
	[1.391]	[0.439]	(0.981)	[0.439]	[1.885]	(1.000)	[1.885]	[0.462]	(0.445)
Nigeria	-25.145	-24.308	0.011	-24.308	-35.749	0.000	-35.749	-24.595	0.081
	[2.274]	[1.621]	(0.967)	[1.621]	[7.766]	(1.000)	[7.766]	[2.428]	(0.221)
South Africa	-21.479	-21.989	0.054	-21.989	-31.437	**0.354**	-31.437	-20.506	0.069
	[5.546]	[2.057]	(0.542)	[2.057]	[12.466]	(0.000)	[12.466]	[2.585]	(0.427)
Panel E: S&P500 stock returns									
Botswana	-8.746	-11.071	0.003	-11.071	-223.892	0.001	-223.892	-9.509	0.000
	[2.731]	[5.319]	(0.991)	[5.319]	[486.258]	(0.998)	[486.258]	[4.964]	(1.000)
Egypt	-16.162	-15.975	0.098	-15.975	-22.881	0.000	-22.881	-16.954	0.058
	[1.375]	[1.006]	(0.225)	[1.006]	[6.107]	(1.000)	[6.107]	[3.010]	(0.643)
Kenya	-16.956	-17.729	0.013	-17.729	-20.711	0.068	-20.711	-15.698	0.093
	[3.297]	[3.294]	(0.984)	[3.294]	[5.876]	(0.514)	[5.876]	[0.908]	(0.267)
Morocco	-10.392	-10.036	0.026	-10.036	-13.233	**0.721**	-13.233	-10.096	0.085
	[0.912]	[0.264]	(0.813)	[0.264]	[1.800]	(0.000)	[1.800]	[0.426]	(0.342)
Nigeria	-24.896	-24.118	0.031	-24.118	-34.753	0.000	-34.753	-24.465	0.000
	[2.114]	[1.507]	(0.763)	[1.507]	[7.219]	(1.000)	[7.219]	[2.323]	(1.000)
South Africa	-19.869	-21.848	0.008	-21.848	-31.042	**0.439**	-31.042	-20.448	0.047
	[1.796]	[2.002]	(0.984)	[2.002]	[12.131]	(0.000)	[12.131]	[2.545]	(0.713)

Table 5.14 (continued)

	$CoVaR_{[1]}$	$CoVaR_{[2]}$	H_0 / H_1	$CoVaR_{[2]}$	$CoVaR_{[3]}$	H_0 / H_1	$CoVaR_{[3]}$	$CoVaR_{[4]}$	H_0 / H_1
Panel F: EUXTX stock returns									
Botswana	-8.785	-11.098	0.031	-11.098	-221.840	0.000	-221.840	-9.578	0.025
	[2.774]	[5.386]	(0.932)	[5.386]	[488.764]	(1.000)	[488.764]	[5.062]	(0.942)
Egypt	-15.945	-15.772	0.088	-15.772	-22.161	0.005	-22.161	-16.161	0.051
	[1.272]	[0.931]	(0.348)	[0.931]	[5.649]	(0.989)	[5.649]	[1.486]	(0.657)
Kenya	-17.032	-17.822	0.024	-17.822	-20.876	0.059	-20.876	-15.743	0.003
	[3.376]	[3.373]	(0.971)	[3.373]	[6.016]	(0.660)	[6.016]	[0.930]	(0.997)
Morocco	-10.513	-10.127	0.086	-10.127	-13.594	0.000	-13.594	-10.192	0.050
	[0.989]	[0.286]	(0.475)	[0.286]	[1.952]	(1.000)	[1.952]	[0.462]	(0.661)
Nigeria	-25.045	-24.232	0.011	-24.232	-35.352	**0.795**	-35.352	-24.595	0.000
	[2.210]	[1.575]	(0.992)	[1.575]	[7.548]	(0.000)	[7.548]	[2.428]	(1.000)
South Africa	-19.918	-21.929	0.008	-21.929	-34.266	**0.198**	-34.266	-20.506	0.006
	[1.824]	[2.034]	(0.990)	[2.034]	[12.321]	(0.000)	[12.321]	[2.585]	(0.988)

Notes: The table reports results for test of 'shift-contagion' in African stocks for downside conditional-value-at-risk (CoVaR) using the Kolmogorov-Smirnoff (KS) statistics. Standard deviations (%) for CoVaR are in squared brackets. P-values for the K-S statistic are in brackets. CoVaR subscripts [1], [2], [3], and [4], respectively represent pre-crises, phase I, phase II, and post-crisis periods.

We observe shock propagation from some exchange rate and developed equity markets to African stocks only in Phase II and the post-crisis periods. For Phase II, spillover is identified from the EUR to Morocco, USD to South Africa, FTSE100 to Egypt and South Africa, S&P500 to Morocco and South Africa, and EUSTX to Nigeria and South Africa. In the post-crisis period, only shock from the USD exchange rate to Kenya is observed. The result is somehow similar to Daryl and Biekpe (2002) who find evidence of contagion during the 1997 Asian crisis to South Africa, Morocco, Egypt, and Namibia. Again, Giovannetti and Velucchi (2013) observed that shocks from the collapse of Lehman Brothers had more relevant impact on African stock markets; and that South Africa and Nigeria received immediate impact, with shocks persistent even after the period of the Lehman Brothers. More closely related to our findings (especially, the evidence of Phase II spillover effects) is the observation by Beck *et al.,* (2009) that propagation of shocks from the GFC had a second round effect in Africa. Thus, the impact of the GFC to African economies was not through the credit crunches and liquidity freezes in Phase I, but rather through the global recession that followed into the second phase. The findings brings to the fore that, though evidence for the full sample (see Table 5.13) and Phase I (see Table 5.15) show no signs of African stock markets affected by (extreme) downward fluctuations in foreign exchange rates and global equity markets, same cannot be said for acute periods of 2007-2009 crisis. This also, brings to mind that related studies that focus on only full sample and Phase I estimation results may not present a complete picture on the dynamic interactions among markets.

The evidence of contagion during the acute phase of the 2007-2009 crisis is found for markets that are known to be highly integrated in Africa, though the levels of integration differ. The increased susceptibility of these markets to contagion effects may also rest on their market's liquidity levels and the real sector of their economies. South Africa and Egypt remain the largest and most liquid markets in Africa, and therefore are likely to be the most integrated with global capital flows. It would then be expected that these markets would be the most susceptible to contagion. Morocco and Nigeria are a bit difficult to explain. However, the two markets are relatively large (Nigeria being the largest in West Africa) and well-traded among emerging markets, although not at the levels of Egypt and South Africa.[73] Whilst the above reasons may sound plausible, giving that the extent of markets integration in Africa is not high as compared to their developed counterparts – other channels may account for the spillovers. For instance, stock markets in Africa do not have higher exposure to risks emanating from complex derivative instruments. They have relatively less free-float shares and although they are open to foreign investor participation, the levels of openness are relatively low. Further, stock markets in Africa do not have large numbers of listed firms that are also in the international register – and thus, the likelihood of listed corporates in the international register to carry-on global risks to the local markets is limited.

The deduction is that despite the establishment of second round contagion risk, it thus appears the possibility of Africa to suffer such spillover effects during crisis through the equity market is not intense. Intuitively, the spread of contagion from the GFC to Africa is non-homogenous for individual countries. Commodity driven economies such as Nigeria, South Africa, Botswana, and Kenya suffered from drops in export prices and volumes, as well as demand for commodities, among other factors. Simatele (2014) indicates that the negative effects of the GFC on African markets could be attributed to the effects on trade balances possibly arising from export demand shocks and price movements of key commodities. For instance, contagion to the South African Johannesburg Stock Exchange (JSE) was mainly through a deteriorating overall economy with the slump in economic aggregates heightening pressure on the country's balance of payment with consequential effects on domestic exchange rates, overall gross domestic product (GDP) and financial sectors, without corresponding increases in portfolio investments flows (Simatele, 2014). In the post Lehman Brothers collapse (Phase II of the crisis) between May 2008 and March 2009, South Africa's Johannesburg All-Share-Index (JALSH) index fell by about 46% and the rand

[73] Morocco also has the same weight in the IFC index as Egypt.

depreciated by 23% against the U.S. dollar. The result was dramatic increases in the cost of capital, and a severe contraction in lending, which led to sharp downturns in the retail and manufacturing sectors. In Botswana lower diamond sales to financially depressed European markets during the crisis made the domestic economy highly vulnerable to shifts in global economies that consume the country's diamond (see also Ahmed and Mmolainyane, 2014). Since the Botswana market has higher weightings towards the diamond industry the consequential effects on the local bourse was noticeable.

A second possible channel of shock spillover was the large-share of foreign-owned banks in the continent. The financial distress among parent foreign banks in Western Europe led to some capital withdrawal and calling in of loan advances to African subsidiaries, with equity investments suffering additional contagion risk – especially in markets where banks advanced loans to clients to purchase shares (e.g. Nigeria) (see also, Beck *et al.,* 2009). However, this channel could not cause much havoc as European banks have low equity levels in Africa and also the overall dependence on foreign subsidiaries in Africa on parent bank funding is low. The dilemma on the plausibility of contagion to Africa via the banking sector is still an area that requires further attention. At one breadth the idea towards pan-Africa banks have the tendencies to mitigate contagion risk from European banks, however, to the extent that economies from where these banks have their roots – mostly Nigeria and South Africa – are also unsheltered from the crisis the possibility of additional contagion cannot be discounted – see also Beck *et al.,* (2009).

Another channel for contagion risk to African stock markets was the drop in international capital flows. The advent of the crisis saw a reverse of the hitherto African economies benefit from the global liquidity glut as there were sharp declines in foreign direct investments and increases in the flight of portfolio investments. Simatele (2014) observes that despite the increases in private capital flows into Sub-Saharan Africa (SSA) in the early days of the 21st century, the advent of the GFC registered some declines due to increased investor risk-aversion, tighter global credit conditions, and developments in the bond markets. For instance, at the peak of the crisis in 2008, no African country issued bonds and already existing ones were either cancelled or postponed (Kasekende *et al.,* 2009; Brambila-Macias and Massa, 2010).– especially Kenya and Ghana postponed their bond issues in 2008. However, the International Monetary Fund (IMF) observes that boom-bust cycle in private financial inflows was less marked than in other regions, largely due to the high share of foreign direct investment over other more volatile forms of private capital. Remittances also fell only slightly and official financing flows increased in response to efforts by the IMF and other agencies to scale up support in response to the crisis (IMF 2010). The IMF African Economic Outlook report released in 2010 suggests that during the GFC, movements in the terms of trade outweighed the impact of the reversal in private capital flows for many countries. For oil producers, a massive deterioration in their terms of trade, equivalent to 27 percent of GDP in 2009, was exacerbated by the reduced availability of private external financing. For non-oil producers, however, terms of trade gains in 2008–2009 largely offset the financing shock. With multilateral institutions scaling up support, an increase in official financing partially compensated for the reduction in private capital inflows during the crisis and the share of official flows in total financing to the region rose sharply. Although, it thus appears the declines in international capital flows were not seen to be substantial during the acute phase of the crisis, because of the small size of the African financial system, even a small absolute drop in capital inflows could have a relatively large effect on its markets (Beck *et al.,* 2009). Aside the above, shocks could also be propagated through other indirect channels such as changes the overall international regulatory architecture and the real economy (see also, Beck *et al.,* 2009; Ncube *et al.,* 2014; Simatele, 2014).

In summary, it appears the discourse on what may constitute the possible channels of global shock transmission to Africa is unsettled: is it predominantly through commodities and real sectors of the economy or the stock market route? This ambiguity underscores the significance of the proposed channels of transmission in Table 5.0 and model 5.1. On account that we do not identify intense and widespread episodes of contagion to Africa via the equity markets, we wish to agree with Beck *et al.,* (2009: 12) "*that while financial market underdevelopment seems, prima-facie, to help countries isolate themselves against immediate contagion; it also reduces the ability of the real economy to cushion the impact of the crisis*". *Implicitly, we argue that despite the notion that a well-integrated and highly developed market may present fertile grounds for shocks spillover, African economies must continue the integration agenda of its segmented equity markets. However, the degree and extent of both inter- and intra-regional integration ought to be pegged at certain optimal levels in order to reap benefits from scale economies.* Such aggressive pursuit of integration will not only help in risk diversification but also help smooth the impact of shocks.[74]

[74] See also Beck *et al.,* (2009).

Given that some evidence of contagion is established not in Phase I but Phase II (which is also part of the crisis period) we are unable to conclude with precision whether or not the 'shift-contagion' theory holds for African stock markets. However, we can conclude that African stock markets were completely insulated from adverse shocks of the global financial crisis at the initial stage, and only suffered marginal effects during the acute stream of the crisis. This is consistent with the view that global shocks propagation to developing markets may stagger during crisis and intensify post- (see also Dungey and Gajurel, 2015). *A practical implication from the results is that given the relatively scarce resources and levels of technological know-how available to African governments, efforts to wean the continent's equity markets from adverse effects of global market crashes should be geared towards plans and programmes to mitigate the shocks not at the early stages but latter stages, where the effects to Africa could be pronouncedly felt.*

5.4 Conclusion

In financial risk management, tail-dependence has been noted to be very useful in ascertaining whether two markets boom or crash together. On account of the reality of leptokurtic innovations or skewed distributions of financial time series data, applying techniques that rely on the normality assumptions may be misleading or inappropriate for risk measures in portfolio analysis. In this chapter, we examined the dependence structure and (extreme) downside spillover effects among stock markets and between stock markets and exchange rates. We used data of six African stock markets (Egypt, Nigeria, South Africa, Morocco, Kenya, and Botswana), the EUR and USD foreign exchange rates against domestic currency, and four developed equity markets – EUSTX, FTSE100, Asia ex.Japan, and S&P500. The sample period spans from January 2003 to February, 2016. Four different copula functions namely, normal Gaussian, Student-t, Gumbel and Rotated Gumbel are used to examine the dependence structure of the sampled markets in both the static and time-varying frameworks. Subsequently, using the parameters for the copulas, we estimated spillover effects across the markets based on conditional value-at-risk (CoVaR) of the markets and used the Kolmogorov-Smirnoff bootstrap test statistics to confirm evidence of spillovers. In finding evidence or otherwise of the existence of the 'shift-contagion' theory by Forbes and Rigobon (2002) in Africa, we disaggregated the sample data into sub-segments to account for the two phases of the 2007-2009 global financial crisis. Lastly, we applied the Toda-Yamamoto Granger causality test to examine evidence of interdependences among the considered markets.

The empirical results show evidence of generally negative and marginal positive dependencies between exchange rates and the African stock markets. The evidence of negative dependence between stocks and exchange rates implies that higher (lower) equity prices are accompanied with depreciation (appreciation) of domestic currencies, expressed in USD or EUR terms. The reverse may hold for market pairs with significant positive dependencies. A common observation across all time paths for the stock-exchange rate dependence shows fast reducing upper and lower-tail dependencies of all markets with the USD and EUR exchange rates over time, except for South Africa/USD pair where there was a sudden sharp increase in upper tail dependence around 2010 and 2011; and the Morocco/EUR pair where all graphs depict average signs of mean-reversion over time. The non-homogenous nature of the time-varying correlations and usually moving from positive to negative (averagely very low, i.e. less than 0.5) suggests the equity markets partial segmentation from price risks of the USD and EUR exchange rate similar to Kodongo and Ojah (2011).

Except for Egypt, we find evidence of positive significant dependencies between all African markets and their developed counterparts. In the case of constant tail dependence, all market pairs exhibit both lower and upper tail dependence (as shown by the rotated Gumbel and Gumbel parameters, respectively). This dependency structure suggests that African stock markets stand to lose (gain) in bear (bull) seasons of the developed markets. This rather condenses potential gains from diversification. In the time-varying setting, the dependent structure (left- or right-tail) shown is quite similar to that shown in the static framework for all market pairs. The significant similarity is that, in both static and time-varying frameworks, all market pairs show higher persistence time-varying volatility in both left and right tail dependence, since mostly the persistence dependence parameters, β is significant, but the α is non-significant largely.

Though, no spillover effects are found for the full-sample period, disaggregating the data into sub-samples show contrasting results. We observe shock propagation from some exchange rate and developed equity markets to African stocks only in Phase II and the post-crisis periods. For Phase II, spillover is identified from the EUR to Morocco, USD to South Africa, FTSE100 to Egypt and South Africa, S&P500 to Morocco and South Africa, and EUSTX to Nigeria and South Africa. In the post-crisis period, only shock from the USD exchange rate to Kenya is observed. The evidence of contagion during the acute phase of the 2007-2009 crisis is found for markets that are known to be highly integrated in Africa, though the levels of integration are not the same. The findings are consistent with the view that global shocks propagation to developing markets may stagger during crisis and intensify post-crisis. A practical implication from the results is that given the relatively scarce resources and levels of technological know-how available to African governments, efforts to wean the continent's equity markets from adverse effects of global market crashes should be geared towards plans and programmes to mitigate the shocks not at the early stages but latter stages, where the effects to Africa could be prominently felt.

Further we argue that despite the notion that a well-integrated and highly developed market may present fertile grounds for shocks spillover, African economies must continue the integration agenda of its segmented equity markets. However, the degree and extent of both inter- and intra-regional integration ought to be pegged at certain optimal levels in order to reap benefits from scale economies. In light of the above, we implore further studies not to only examine the channels of shock transmission outlined in Table 5.0 and model 5.1 but also find answers to the following questions: (i) *How have well integrated African financial markets fared in the midst of global shocks?(ii) At what stage of integration, interdependence, and development can African markets expect to experience the benefits of integration and interdependence, without the fear of contagion?(iii) Should African financial markets that are not yet integrated be dissuaded from integrating due to risk dimensions of globalization and integration?(iv)Would the adherence to (iii) not preclude Africa from sharing in the genuine benefits of globalization and modernization?*

Among the possible channels for further exploration are: first, considering the relative poverty and underdevelopment nature of the African economy, it would be interesting to find out how information flow between Africa and the developed world could affect flow of funds across borders and necessitate home bias[75] (see Albuquerque *et al.,* 2009). For this reason, the impact of the amount of telephone traffic and ratio of value of imports of newspapers from the global economy – example US, (quantified in the US currency) to domestic GDP (see Bekaert *et al.,* 2014), and geographic distance between a country and the US (see Bekaert *et al.,* 2014) could be examined. Second, because financial and economic integration largely result in susceptibility to shocks, the inclusion of trade and financial openness in the transmission mechanism model may be a laudable idea.[76] Thirdly, to

[75] Home bias refers to the likelihood for investors to invest in domestic markets rather than foreign markets even when there are greater diversification opportunities.
[76] Kaminsky and Reinhart (2000) and Forbes and Chinn (2004) align trade openness with contagion and spillovers.

address the shortfall identified in Pritsker (2000) about how dealer large financial institutions in the financial markets can act as conduits for shock spillover[77], we propose for further studies to consider two proxies of banks in Africa to explore the role of the banking sector in transmitting global shocks to Africa's financial markets. First, equity prices of banks in a domestic African country listed in either a local stock exchange or an international register; and second the Bank for International Settlements data measuring the degree of claims of domestic banks to banks in U.S or the rest of the world by way of loans, deposits, or other assets could be used. Bekaert *et al.,* (2014) note that such exposure affects the domestic banking sector directly and indirectly affects other stocks.

References

Abadie, A., (2002). Bootstrap tests for distributional treatment effects in instrumental variables models. *Journal of American Statistical Association*, 97: 284–292.

Abdalla, I. S. A., Murinde, V., (1997). Exchange rate and stock price interactions in emerging financial markets: Evidence on India, Korea, Pakistan, and Phillipines. *Applied Financial Economics*, 7: 25-35.

Adjasi, C. K., Biekpe, N. B. and Osei, K. A. (2011). Stock prices and exchange rate dynamics in selected African countries: A bivariate analysis. *African Journal of Economic and Management Studies*, 2(2): 143-164. doi:10.1108/204007001111/65623.

Adler, M., Dumas, B., (1983). International portfolio choice and corporation finance: A synthesis. *Journal of Finance* 38: 925–984.

Adrian, T., Brunnermeier, M.K., (2011). CoVaR. NBER working paper series, WP/17454.

Aggrawal, R. (1981). Exchange rates and stock prices: A case study of the US capital markets under floating exchange rates. *Akron Business Economic Review*, 12: 7-12.

Ahmed, D.A., Mmolainyane, K.K., (2014). Financial integration, capital market development and economic performance: Empirical evidence from Botswana. *Economic Modeling*, 42:1-14.

Alagidede, P., (2008). African stock market integration: Implications for portfolio diversification and international risk sharing. *Proceedings of the African Economic Conference* 2008, p. 26 – 54.

Alagidede, P., Panagiotidis, T. and Zhang, X. (2011). Causal relationship between stock prices and exchange rates. *The Journal of International Trade and Economic Development*, 20: 67-86.

[77] Pritsker (2000) asserts that heavily concentrated markets usually encounter liquidity challenges emanating from shocks spillover from dealer firms.

Albuquerque, R., Bauer, G.H., Schneider, M., (2009). Global private information in international equity markets. *Journal of Financial Economics,* 94:18-46.

Aloui, R., Aissa, M.S.B., Nguyen, D.K., (2011). Global financial crisis, extreme interdependence, and contagion effects: The role of economic structure? *Journal of Banking and Finance* 35:130 – 141.

Ane, T., Labidi, C., (2005). Spillover effects and conditional dependence. *International Review of Economics and Finance, 15:417-442.*

Artzner, P.; Delbaen, F.; Eber, J. M.; Heath, D. (1999). Coherent measures of risk. *Mathematical Finance,* 9: 203–228.

Baur, D. G. (2013). The structure and degree of dependence: A quantile regression approach. *Journal of Banking and Finance*, 37: 786-798.

Beck, T., Fuchs, M., Uy, M., (2009). Finance in Africa: Achievements and challenges. *Policy Research Working Paper – 5020, the World Bank Africa Region Finance and Private Sector Development Department*, Auguts, 2009, pp. 1-39.

Bekaert, G., Campbell, R.H, Ng, A., (2005). Market integration and contagion. *Journal of Business* 78:39-70.

Bekaert, G., Erhmann, M., Fratzscher, M., (2014). The global crisis and equity market contagion. *The Journal of Finance*, Vol. LXIX: 2597-2649.

Bhatti, M.I., Nguyen, C.C., (2012). Diversification evidence from international equity markets using extreme values and stochastic copulas. *Journal of International Financial Markets, Institutions & Money*, 22: 622-646.

Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L., (2012). Econometric measures of systemic risk in the finance and insurance sectors. *Journal of Financial Economics* 104:535–559

Bisias, D., Flood, M., Loo, A.W., Valavanis, S., (2012). A survey of systemic risk analytics. *Office of Financial Research, US Department of the Treasury*, Working paper #1.

Boako, G., Omane-Adjapong, M., Frimpong, J.M. (2016). Stock returns and exchange rate nexus in Ghana: A Bayesian quantile regression approach. *South African Journal of Economics*, 84: 149-179.

Brambila-Macias, J., Massa, I., (2010). The global financial crisis and Sub-Saharan Africa: The effects of showing private capital inflows on growth. *African Development Review*, 22:366-377.

Branson, W.H., (1983). Macroeconomic determinants of real exchange rate risk. In R. J. Herring, (ed), *Managing Foreign Exchange Risk*. Cambridge: Cambridge University Press, XIV, 235

Breymann, W., Dias, A., Embrechts, P., (2003). Dependence structures for multivariate high-frequency data in finance. *Quantitative Finance* 3:1–16.

Calvo, G.O., (1999). Contagion in emerging markets: When Wall Street is a carrier. Mimeo, the University of Maryland.

Celik, S., (2012). The more contagion effect on emerging markets: The evidence of DCC-GARCH-model. *Economic Modeling,* 29(5): 1946-1959.

Cenedese, G., Payne, R., Sarno, L., Valente, G. (2015). What do stock markets tell us about exchange rates? A Working Paper, pp. 1-66. Available at papers.ssrn.com.

Chkili, W., Nguyen, D. K. (2014). Exchange rate movements and stock market returns in a regime switching environment: Evidence for BRICS countries. *Research in International Business and Finance*, 31: 46-56.

Chkili, W., Aloui, C., Masood, O. and Fry, J. (2011). Stock market volatility and exchange rates in emerging countries: A Markov-state switching approach. *Emerging Markets Review*, 12: 272-292.

Claessens, S., Della, A,G., Igan, D., Laeven, L., (2010). Cross-country experiences and policy implications from the global financial crises. *Economic Policy*, 25(62):267-293.

Cho, J.-W., Choi, J.H., Kim, T., Kim, W., (2016). Flight-to-quality and correlation between currency and stock returns. *Journal of Banking and Finance,* 62:191–212.

Chow, E. H., Lee, W. J., Solt, M. S. (1997). The exchange rate risk exposure of asset returns. *Journal of Business*, 70: 105-123.

Corsetti, G., Pericoli, M., Sbracia, M., (2005). Some contagion, some interdependence more pitfalls in tests of financial contagion. *Journal of International Money and Finance*, 24:1177-1199.

Creal, D., Koopman, S.J., Lucas, A., (2013). Generalized autoregressive score models with applications. *Journal of Applied Econometrics*, 28: 777-795.

Daryl, C., Biekpe, N., (2002). Contagion: A fear for African markets? *Journal of Economics and Business* 55: 285 – 297.

Delatte, A-L., Lopez, C., (2013). Commodities and equity markets: Some stylized facts from Copula approach. *Journal of Banking and Finance*, 37: 5346-5356.

Diamandis, P. F., Drakos, A. A., (2011). Financial liberalization, exchange rates, and stock prices: Exogenous shocks in four Latin American countries. *Journal of Policy Modeling*, 33: 381-394.

Dornbusch, R., Fischer, S., (1980). Exchange rates and the current account. *American Economic Review,* 70: 960–971.

Dungey, M., Gajurel, D., (2015). Contagion and banking crisis – international evidence for 2007-2009. *Journal of Banking and Finance*, 60: 271-283.

Embrechts, P., McNeil, A., Straumann, D., (2002). Correlation and dependence in risk management: Properties and pitfalls M.A.H. Dempster (Ed.) Risk Management: Value-at-Risk and Beyond, Cambridge University Press, Cambridge (2002) pp. 176-223.

Frankel, J. A. (1983). Monetary and portfolio-balance models of exchange rate determination. In J. S. Bhandari and B. H. Puntam (eds), *Economic Interdependence and Flexible Rates*. Cambridge, MA: MIT Press, Pp. xviii, 547, Index. Paper. ISBN 0-262-02177-3.

Forbes, K.J., Chinn, M.D., (2004). A decomposition of global linkages in financial markets over time. *The Review of Economics and Statistics*, 86 (3): 705 – 722.

Forbes, K.J., Rigobon, R., (2002). No contagion, only interdependence: Measuring stock market co-movements. *The Journal of Finance*, LVII: 2223 – 2261.

Giovannetti, G., Velucchi, M., (2013). A spill-over analysis of shocks from U.S, UK and China on African financial markets. *Review of Development Finance* (3): 169-179. DOI: http://dx.doi.org/10.1016/j.rdf.2013.10.002

Girardi, G., Ergün, A.T., (2013). Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of Banking and Finance* 37:3169–3180.

Granger, C.W. J., Huang, B.-N., Yang, C.W. (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.

Griffin, J. M. and Stulz, R. (2001). International competition and exchange rate shocks: A cross country industry analysis of stock returns. *The Review of Financial Studies*, 14: 215-241.

He, Z., Maekawa, K., (2001). On spurious Granger causality. *Economics Letters*, 73:307-313.

Ho, L.-C., Huang, C.-H. (2015). The nonlinear relationships between stock indexes and exchange rates. *Japan and the World Economy*, pp. 1-18.

Hu, L., (2006). Dependence patterns across financial markets: A mixed copula approach. *Applied Financial Economics*, 16: 717-729.

Hussain, M.N., Mlambo, K., Oshikoya, T., (2002). Global financial crisis: An African perspective. *African Development Review*, 11(2):199-232.

IMF (2010). Africa's private capital inflows resilient in crisis. *IMF Regional Economic Outlook Report,* April, 23, 2010.

Joe, H., (1997). Multivariate models and dependence concepts. In: Monographs in Statistics and Probability 73. Chapman and Hall, London.

Kaminsky, G. L., Reinhart, C. M. (1999). The twin crisis: The causes of banking balance-of-payments problems. *American Economic Review*, 89: 473-500.

Kaminsky, G., Reinhart, C., (2000). On crisis, contagion, and confusion. *Journal of International Economics,* 51: 145-168.

Kanas, A., (2000). Volatility spillovers between stock returns and exchange rate changes: international evidence. *Journal of Business Finance and Accounting*, 27(3): 447-466.

Kasekende, L., Ndikumana, L., Taoufik, R., (2009). Impact of the global financial and economic crisis on Africa. *African Development Bank Working Paper Series*, 96.

Katechos, G., (2011). On the relationship between exchange rates and equity returns: A new approach. *Journal of International Financial Markets, Institutions and Money*, 21: 550-559.

King, M., Wadhawani, S., (1990). Transmission of volatility between stock markets. *Review of Financial Studies*, 3: 5-33.

Koenker, R., Bassett, G., (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society*, 46 (1): 33-50.

Kodres, L.E., Pritsker, M., (1999). A rational expectations model of financial contagion. *FEDS Working Paper* 1998-48, the Federal Reserve Board.

Kodongo, O., Kalu, O., (2011). Foreign exchange risk pricing and equity market segmentation in Africa. *Journal of Banking and Finance*, 35: 2295-2310.

Kose, M.A., Yi, K.M., (2001). International trade and business cycles? Is vertical integration the missing link? *American Economic Review Papers and Procedings*, 371-375.

Kose, M.A., Otruk, C., Prasad, E.S., (2008). Global business cycles: Convergence or decoupling? *IMF Working Paper*, No. 08/143.

Koulakiotis, A., Kiohos, A., Babalos, V., (2015). Exploring the interaction between stock price index and exchange rates: An asymmetric threshold approach. *Applied Economics*, 47(13): 1273-1285.

Krugman, P., (1991). Geography and Trade. *The MIT Press, Cambridge, M.A.*

Lin, F., (2011). Tail dependence between stock index returns and foreign exchange rate returns—A Copula approach. Available at SSRN: <http://ssrn.com/abstract=1931726> or <http://dx.doi.org/10.2139/ssrn.1931726>.

Liu, L., Wan, J., (2012). The relationship between Shanghai stock market and CNY/USD exchange rate: New evidence based on cross-correlation analysis, structural cointegration and non-linear causality test. *Physica A*, 391: 6051-6059.

Louis, K., Leonce, N., Taufic, R., (2009). Impact of global financial and economic crisis on Africa. *Working Paper Series, No. 96, African Development Bank, Tunis*, 36pp.

Mackowiak, B., (2007). External shocks, U.S. monetary policy and macroeconomic fluctuations in emerging markets. *Journal of Monetary Economics*, 54(8): 2512-2520.

Markowitz, H., 1952. Portfolio selection. *Journal of Finance* 7:77–91.

MD. Mahmudul, A., MD. Gazi, S. U., Khan, M.R.T., (2011). The relationship between exchange rates and stock prices: Empirical investigation from Johannesburg stock exchange. *Emerging Economics*, 3: 2-10.

Mendes, V.M., Souza, R.M., (2004). Measuring financial risk with copulas. *International Review of Financial Analysis, 13:27-45.*

Mensi, W., Hmmoudeh, S., Reboredo, C.J, Nguyen, D.K., (2014). Do global factors impact BRICS stock markets? A Quantile regression approach. *Emerging Markets Review, 19:1-17.*

Michelis, L., Ning, C., (2010). The dependence structure between the Canadian stock market and the USD/CAD exchange rate: A copula approach. *Canadian Journal of Economics* 43:1016–1039.

Mishkin, F.S., (2011). Over the cliff: From the subprime to the global financial crisis. *Journal of Economic Perspectives*, 25(1):2920-2937.

Mlambo, C., Maredza, A., Sibanda, A. (2013). Effects of exchange rate volatility on the stock market: A case study of South Africa. *Mediterranean Journal of Social Sciences*, 14: 561-570.

Moore, T., Wang, P., (2014). Dynamic linkage between exchange rates and stock prices. Evidence from developed and emerging Asian markets. *International Review of Economics and Finance*, 29: 1-11.

Ncube, M., Ndou, E., Gumata, N., (2012). How are the US financial shocks transmitted into South Africa? Structural VAR Evidence. *African Development Bank Paper* No. 157.

Ncube, M.., Brixiova, Z., Meng, Q., (2014). Can intra-regional trade act as a global shock absorber in Africa? *Working Paper Series African Development Bank*, No. 198, Febuury 2014.

Nelsen, R.B., (2006). An Introduction to Copulas. Springer-Verlag, New York.

Ning, C., (2010). Dependence structure between the equity market and the foreign exchange market – A copula approach. *Journal of International Money and Finance* 29, 743–759.

Patton, A.J., (2006). Modelling asymmetric exchange rate dependence. *International Economic Review* 47 (2): 527–556.

Patton, A., (2012). A review of copula models for economic time series. *Journal of Multivariate Analysis*, 110:4–18.

Phylaktis, K., Ravazzolo, F., (2005). Stock prices and exchange rate dynamics. *Journal of International Money and Finance*, 24: 1031-1053.

Pourkhanali, A., Kim, J-M., Tafakori, L., Fard, F.A., (2016). Measuring systemic risk using vine-copula. *Economic modelling,* 53: 63-74.

Pritsker, M., (2000). The channels of contagion. *The Contagion Conference*. Available at: siteresources.worldbank.org/INTMACRO/Resources.

Reboredo, J.C., Ugolini, A., (2015). Systemic risk in European sovereign debt markets: A CoVaR-copula approach. *Journal of International Money and Finance,* 51:214–244.

Reboredo, J.C., Rivera-Castro, M., Ugolini, A., (2016). Downside and upside risk spillovers between exchange rates and stock prices. *Journal of Banking and Finance,* 62:76-96.

Senbet, L.W., Gande, A., (2009). Financial crisis and stock markets: Issues, impact, and policies. *Annual Conference of the Dubai Economic Council, Dubai.* Publications de l'Institut Statistique de l'Université de Paris 8: 229–231.

Sklar, A., (1959). Fonctions de Riépartition á n Dimensions et Leurs Marges.

Simatele, M., (2014). Reflections on the impact of the financial crisis on sub-Saharan Africa. *Africa Growth Agenda*, 18-24.

Sheu, H-J., Cheng, C-L., (2012). Systemic risk in Taiwan stock market. *Journal of Business Economics and Management,* 13(5): 895-914.

Solnik, B., (1974). Why do not diversify internationally rather than domestically. *Financial Analyst Journal* 30:48–54.

Stolbov, M., (2014). The Causal Linkages between sovereign CDS prices for the BRICS and major European economies. *Economics Discussion Paper* No. 2014 -9. Available online at www.economics-ejournal.org/economics/discussionpapers/2014-9.

Toda, H.Y., Yamamoto, Y., (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, 66: 225-250.

Tsai, I.-C., (2012). The relationship between stock price index and exchange rate in Asian markets. A quantile regression approach. *Journal of International Financial Markets Institutions & Money*, 22: 609-621.

Ulku, W., Demirci, E., (2012). Joint dynamics of foreign exchange and stock markets in emerging Europe. *Journal of International Financial Markets, Institutions and Money*, 22: 55-86.

World Economic Forum, (2009). The global enabling trade index report. *World Economic Forum, Geneva.*

Zhao, H. (2010). Dynamic relationship between exchange rate and stock price: Evidence from China. *Research in International Business and Finance*, 24: 103-112.