Stock Market Connectedness in Africa: Do Regional or Global Effects Dominate?

Iswat Olajumobi Oladele

Economics Department

University of Strathclyde, Glasgow

February 29th, 2024.

This thesis is the result of the author’s original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree. The copyright of this thesis belongs to the author under the terms of the United Kingdom Copyright Acts as qualified by University of Strathclyde Regulation 3.50. Due acknowledgement must always be made of the use of any material contained in, or derived from, this thesis.

Abstract

How connected are African countries' financial markets, both within the African continent and within global markets and why does this matter? This paper examines the concept of connectedness and its relevance, using Diebold & Yilmaz's (2012, 2014) network methodology. Even though several studies have been conducted using the Diebold & Yilmaz's (2012, 2014) network methodology, this methodology has not been used to assess some of the largest African stock markets. Existing evidence shows that, on average, African equity markets are net receivers of both return and volatility spillovers. There is, however, a gap in knowledge as to the validity of this, when hit by financial crises. Building on this, this paper employs a quantitative aggregation method for a closer analysis of the connectedness table, using daily data from January 3, 2011 to August 9, 2023. This approach unveils that some shocks originating from stock markets per region (Northern, Southern, Eastern and Western Africa) dominate global shocks. Specifically, we find that shocks originating from stock markets in other regions in Africa (regional effects) dominate stock markets in Northern Africa, while shocks originating from global effects are more prominent among stock markets in Southern Africa. In addition, considering the flexibility of return and volatility spillovers and their ability to change over time, this paper projects time-varying estimates of return and volatility spillovers. Comparing two specific crises – the European Sovereign Debt Crisis and the COVID-19 pandemic, this study finds that there were more pronounced volatility spillovers during the COVID-19 pandemic compared to the European Sovereign Debt Crisis. However, return spillovers were more pronounced during the European Sovereign Debt Crisis.

Contents

List of Figures

List of Tables

Preface/Acknowledgements

I would like to acknowledge Jesus Christ, my Lord and Friend for giving me the wisdom, strength, and tenacity to write this research work. I would like to acknowledge the support of my family, friends and church community who were my loudest cheerleaders in this academic sojourn, I would not have made it to the end without you. I appreciate the expertise of my supervisors who were instrumental in directing this research work.

1. Introduction

In an increasingly interconnected global financial system, the presence of macroeconomic connectedness and its associated risks have grown remarkably in the 21st century. The 2007-2009 Global Financial Crisis revealed how financial instability can spread rapidly across closely linked economies and markets. Researchers argue that macroeconomic connectedness has risen due to influential forces such as globalization, deregulation, and technological advancements in trading systems (Diebold & Yilmaz, 2015, Greenwood-Nimmo et al., 2021).

According to Ogbuabor et al. (2016), connectedness manifests in two key forms - real connectedness, which refers to synchronized business cycles among economies, and financial connectedness, which captures the spread of financial contagion globally. Financial connectedness[1] in the global economy has risen due to growing cross-border financial positions, as investors exploit foreign investment opportunities. Specifically, portfolio investments have increased significantly in the last decade.

Greater financial development in emerging market economies has facilitated access to cheaper funding and created opportunities for risk-sharing with connected stock markets, but increased financial development also potentially exposes countries to external vulnerabilities and real/financial contagion. The 2007-2009 Global Financial Crisis (GFC) demonstrated how quickly crises can propagate through interconnected stock markets. From this experience, it can be deduced that high levels of financial connectedness can pose systemic risks and constrain policy options for individual economies, underscoring the need for coordinated regulations and regional collaboration to ensure financial stability.

Recently, Africa has attracted more foreign capital inflows, reaching a record $70.15 billion in FDI by 2021 from $30.6 billion in 2016 (World Bank database, 2023). In addition to this,

[1] Financial connectedness has been defined as the degree to which financial markets are integrated (Billio et al, 2012). Within the context of this paper, we define financial connectedness as the degree to which stock markets are integrated.

regional economic integration reforms have also fostered tighter African connections in the realms of trade, transport, and finance. For instance, the new African Continental Free Trade Area (AFCFTA) aims to promote a unified market for goods and services to spur cross-border business. Similarly, financial markets across the continent have progressively opened to foreign investors and pan-African banks expanding beyond home countries. Furthermore, transport links have been strengthened, thereby enabling greater mobility of people and goods, with the Economic Community of West African States (ECOWAS) now allowing visa-free travel for citizens - a model now being considered by other African economic communities. While further progress is needed, the aforementioned integration efforts have laid a foundation for enhanced intra-regional connectivity and financial ties.

Past studies have analysed financial connectedness using various quantitative methods, including correlation-based metrics, Marginal Expected Shortfall (MES) analysis, and network approaches like Diebold and Yilmaz's (2012, 2014) influential spillover index model. More recently, Antonakakis et al. (2020) advanced a time-varying parameter VAR model to track dynamic connectedness. However, there is still a shortfall in how holistic this approach is, as there are no studies to suggest how this can be applied to stock markets within specific African countries. Previous studies show that while financial connectedness has been studied extensively in relation to the 2007-2009 GFC as well as advanced and some emerging economies such as the EU, Middle East, and G7 countries, there is less analysis of African markets. It is, however, noteworthy that some scholars like Sugimoto et al. (2014), Atenga & Mougoue (2021), Ogbuabor et al. (2016) and Fowowe & Shuaibu (2016) have each examined connectedness in Africa through the lens of the 2007-2009 global financial crisis, 2012 European Sovereign Debt crisis, 2015 oil price shocks and made some notable findings which are relevant to this study. For example, studies conducted by Sugimoto et al. (2014) and Atenga et al. (2021) show that most markets within Africa are more susceptible to impacts of shocks from advanced and emerging economies than they are to shocks originating from elsewhere within Africa. These studies, however, exclude some key African stock markets, limiting the scope of their study.

This thesis adds to knowledge by building on the existing literature to explore the financial connectedness beyond the 2007-2009 GFC as well as a larger representative of African stock markets, including Kenya and Ghana, to determine if global or regional effects dominate and the implications thereafter. First, I use an updated and extended dataset to explore African financial connectedness, extending Atenga& Mougoue (2021) to include the 10 largest African stock exchanges (South Africa, Morocco, Nigeria, Egypt, Botswana, Kenya, Ghana, Tunisia, Mauritius and BVRM) by market capitalization, spanning regional locations in the North, East, West, and South Africa, alongside selected advanced and emerging country stock markets. The period of the European Sovereign Debt Crisis was selected for this study as it affected African economies through the commodity price, export growth and foreign direct investment channels. Second, I use the Diebold & Yilmaz's (2012, 2014) methodology to analyse connectedness beyond past crises to include recent events such as the 2012 European Sovereign Debt Crisis as well as the COVID-19 pandemic. Third, I employ a regional and pan-African aggregations of the bilateral spillovers indicated in the full system connectedness matrix to draw out new insights. This study finds that stock markets located in the North of Africa are more integrated with other African stock markets whereas stock markets located in Southern Africa are more integrated with stock markets in Advanced and Emerging market economies. Northern and Southern Africa are home to the oldest and largest stock markets, highlighting that the older and larger stock markets tend to have more connectedness with stock markets in Africa and the rest of the world.

The remainder of this thesis is structured as follows: Section 2 presents an overview of African stock market development and the associated literature. Section 3 describes the full sample, rolling sample and aggregated network methodology used to quantify spillovers. Section 4 discusses the data and preliminary analysis. Section 5 presents and discusses the empirical results and their implications. Finally, Section 6 concludes with an overall summary of the study, and a summary of the main findings to the aims and objectives of this study, while also highlighting the contribution to knowledge. In summary, I provide the limitations of the study and future recommendations.

2. Overview of the Empirical Literature

The literature on financial connectedness has grown substantially, with influential contributions by Diebold & Yilmaz (2009), Park & Shin (2014), Greenwood-Nimmo et al. (2015), and Ghini & Saidi (2017). Owing to the increased conversation around connectedness, more and more studies have attempted to examine the growing phenomenon. The key themes identified in the literature include- Asymmetries in market connectedness, the influence of macro factors in market connectedness and spillovers, the role of oil in market spillovers and hedging portfolios and the dynamic cross-market connectedness and spillovers.

Studies have explored asymmetries across various markets, highlighting that exogenous shocks such as oil market shocks or the 2007-2009 Global Financial Markets produce asymmetric response in stock market volatility (Wang et al, 2020). Baruník et al. (2017) explored asymmetries among the forex markets of AUD, GBP, CAD, EUR, JPY, and CHF[2] between 2007-2005. The authors adopt the Diebold & Yilmaz (2009) method to measure asymmetric volatility spillovers and find that positive asymmetric spillovers are correlated with the 2007-2009 Global Financial Crisis while negative asymmetric spillovers are correlated with the 2012 European Sovereign Debt Crisis. Furthermore, the authors find that each currency displays different patterns in propagating asymmetric volatility connectedness- CAD, AUD, EUR transmit asymmetric volatility spillovers while GBP, JPY and CHF receive asymmetric spillovers.

Studies have also examined the influence of macro-factors in connectedness and spillovers. The likes of WU (2020), Jayasuriya (2011), Chien (2015) have demonstrated that market size does not play a significant role in the market and once accounted for, connectedness reduces significantly. Wu (2020) and Jayasuriya (2011) shows that the tax, size, stability, and

[2] AUD- Australian Dollar, GBP- Great British Pound, CAD- Canadian Dollar, EUR- Euro, JAP- Japanese Yen, CHF- Swiss Franc

technological advancements have unique impacts on connectedness. (Wu 2020) investigates financial integration among stock markets of ASEAN5 economies with graph theory and var-based method. Their findings reveal that high levels of integration are driven by common global factors and when this is controlled for, connectedness reduces significantly. The authors argue that stock market integration among East and Southeast Asia are not as strong as otherwise believed. Similarly, Jayasuriya (2011) come to a similar conclusion of little to no evidence of integration among Asian stock markets without considering foreign investment returns. The authors examine integration between China's stock market with three neighbour emerging markets from the Asia Pacific region between November 1993 to July 2008.

Likewise, studies have examined the role of oil in market spillovers and hedging. Bouri (2015) explored the role of oil market volatility spillovers on the stocks of oil importing countries. The author finds that volatility spillovers were more pronounced after the 2007-2009 Global Financial Crisis for Jordan with smaller impacts observed for Lebanon. In other words, Jordan responded more to oil shocks than Lebanon. Similarly, Malik & Umar (2019) investigates oil and exchange rate connectedness of major oil importing and exporting countries. The author also finds that oil price shocks resulting for demand and risk significantly contribute to variation in exchange rates. Similar to Bouri (2015), the author finds that connectedness between oil price shocks and exchange rates were more pronounced after the 2007-2009 Global financial Crisis.

Diebold & Yilmaz (2009, 2012, 2014), Antonakakis & Kizys (2015), Awartani et al (2016), Maghyerah et al (2016), Kang et al. (2019), Coskun et al (2023) investigate dynamic cross markets connectedness and spillovers. Diebold & Yilmaz (2009) explore the measurement of return and volatility spillovers based on Cholesky variance decompositions from VAR models, which provide information on the average connectedness effect into a single connectedness measure. In addition, the authors pioneer the spillover index which measures financial connectedness among asset returns and volatilities. To establish the connectedness, the authors adopt the Cholesky framework to examine global stock market return and volatility spillovers over a full sample and a rolling sample analysis of 19 global equity markets across advanced and emerging markets economies between January 1992 - November 2007, utilising daily stock price indices. Results from this analysis show that across the full sample, 36% and 40% of the forecast error variance in return and volatility can be attributed to spillovers, indicating that on average, return and volatility connectedness are relatively of the same magnitude. Additionally, the authors explore the dynamic nature of spillover through the rolling sample analysis, and they observe an increasing trend with no bursts for return spillovers while volatility spillovers display no trend with very clear bursts. While this paper pioneers a new approach towards studying return and volatility spillovers, the calculation of spillovers is based on the Cholesky variance decomposition. Results are therefore not robust across the many alternative feasible orderings of the variables in the VAR. One of the gaps that this study aims to address.

While Diebold & Yilmaz (2009) produced an acceptable result, this study argues that the result was not robust. However, Diebold & Yilmaz (2012) provide a refined methodology, based on generalised variance decompositions which are invariant to the ordering of the variables in the VAR, meaning that estimated spillover effects are also not impacted by the ordering of the various market's stock returns or volatilities. Additionally, the authors provide measures of both total and directional spillovers, providing a holistic view of spillovers as a single and directed index. While the total spillover index gives an understanding of the magnitude of shocks to volatility spillover across major asset classes, the directional spillover measure allows us to observe the direction of volatility spillovers across major asset classes. This improved methodology is used to calculate daily volatility spillovers across the US stock, bond, foreign exchange, and commodities market between January 25, 1999 and January 29, 2010. As a result, the authors find low directional spillovers among the markets considered in their study, with the highest directional spillover received and transmitted by the bond markets to the stock, commodities, and foreign exchange markets.

In their 2014 paper, the authors extend their methodology, developing several connectedness measures built from generalised variance decompositions. They propose that variance decomposition can be defined as weighted, directed networks, bringing in key aspects of connectedness measures adopted in the network literature. They use this novel method to track average and time-varying connectedness among major US financial institutions' stock return volatility between May 1999 and April 2010. The findings of this study evidenced that 78.3% of the forecast error variance in return can be attributed to spillovers, indicating high connectedness among US financial institutions. In their rolling sample analysis, the authors observe a trend of high total volatility connectedness during a financial crisis and a lower total volatility connectedness post-crisis. Their findings reveal that financial institutions with higher levels of connectedness faced increased susceptibility to transmitting spillovers. This is seen with the high pairwise directional connectedness from Citigroup to Bank of America and/or J.P. Morgan. Citigroup's stock spread spillovers to stocks from connected top commercial banks. These findings were also seen across other financial institutions i.e., mortgage finance companies, and insurance companies, which spread trouble to connected financial institutions. While this updated methodology captured some of the data that were not captured in previous studies, it can be argued that the updated methodology worked well in the US market, however, this only calls for questions as to how well this would work if applied to a specific African market.

Similarly, Coskun et al. (2023) applied Diebold Yilmaz's (2012) methodology to examine volatility connectedness among geopolitical oil price risk (GOPRX), clean energy stocks, global equity, and commodity markets between September 2004 to September 2020 across full and rolling sample analysis. Their findings reveal low connectedness among markets as the total connectedness index is 37.4%[3]. They find the GOPRX and the global equity markets to be net transmitters of volatility spillovers, and the gold market to be a net receiver of volatility spillovers, thereby highlighting the leader and follower roles each market plays in the system. With their rolling sample results, the aforementioned authors find peaks in total volatility spillovers corresponding to crisis periods of the Arab Spring which lasted till 2006, the election of President Trump between 2016 and 2017 and the COVID-19 pandemic in 2020.

Similarly, Maghyerah et al. (2016) examined return and volatility spillovers of Sukuk[4] and global bonds with equities between September 2005 and February 2014 with the Diebold & Yilmaz (2012) method. The study shows that 31.7% and 52.9% of forecast error variance across all markets can be attributed to return and volatility spillovers. Additionally, the study found Sukuk to be a net receiver of volatility spillovers from other markets. Similar to Awartani et al. (2016), Maghyerah et al. (2016) also observed high return and volatility spillovers around the crisis period, between 2008- 2009, and 2010-2012 in their rolling sample analysis.

The previous studies have discussed studies situated in foreign settings. However, considering that this study aims to address financial connectedness in Africa beyond the 2007-2009 GFC, it is important to review literatures that speak to the Africa context. Fowowe & Shuaibu examine dynamic spillovers between Nigeria, South Africa and international equity markets between January 2005 and June 2013. Their findings reveal that 43.9% and 32.8% of forecast error variance in return and volatility can be attributed to spillovers, indicating low levels of connectedness between the South African, Nigerian, US and UK Equity markets. Their results are similar to Antonakakis & Kizys (2015) who also find more pronounced spillovers in returns than volatility despite the differences in sample countries. Overall, the authors find the Nigerian

[3] We classify low connectedness to be total spillover index of less than 50% while high connectedness has a total spillover index of more than 70%. This is consistent with the classification of Diebold & Yilmaz (2012, 2014)
[4] Islamic bonds

and South African equity markets more connected with the European equity market. Furthermore, Nigeria and South Africa are both net receivers of return and volatility spillovers from other stock markets included in the study.

Sugimoto et al. (2014), Atenga & Mougoue (2021), and Ogbuabor et al. (2016), among others, have also examined connectedness in Africa. Sugimoto et al. (2014) employ Diebold & Yilmaz's (2009) connectedness measure to explore regional and international spillovers in African financial markets in the wake of the US financial crisis and the European sovereign debt crisis. The authors examine spillovers between seven African stock markets (Egypt, Mauritius, Morocco, Namibia, South Africa, Tunisia, and Zambia), three EU stock markets (France, Germany, UK), three global stock markets (China, Japan, US), two commodities market (gold and petroleum) and two nominal effective exchange rates (Euros and US dollars). The authors find that 38.7% of forecast error variance in returns can be attributed to spillovers, indicating low levels of connectedness among the sample markets. Additionally, the paper finds that return spillovers from the global market have a greater effect than regional return spillovers in African stock markets. In their dynamic analysis, the authors find that return spillovers among African stock markets responded more to the European Sovereign Debt Crisis than the US Subprime Crisis.

Ogbuabor et al. (2016) explore real and financial connectedness among African economies and global economies between 1981Q1-2012Q3, employing Diebold & Yilmaz's (2009) network approach. The authors find high connectedness with a total connectedness index of 71% across both real (output) and financial (return) connectedness. Additionally, in their rolling sample estimate, the authors find real and financial connectedness displaying an increasing trend precrisis, with financial connectedness reacting more persistently than real connectedness, highlighting that financial contagion tends to spread more quickly.

Atenga & Mougoue (2021) conduct a similar analysis as Sugimoto et al. (2014), exploring regional and global spillovers to the African stock market covering periods beyond the 2007-2009 Global Financial Crisis such as the collapse of oil prices, Brexit, and the US-China trade wars. The authors explore return and volatility spillovers between ten African markets (Weamu, Botswana, Egypt, Mauritius, Morocco, Nigeria, South Africa, Tanzania, Tunisia, and Zambia), five developed markets (France, Germany, UK, Japan, and the US), and six emerging markets (Brazil, Hong Kong, Mexico, Russia, India, and China) from January 2007 till September 2019, adopting daily all prices indices for each country. The authors find that 47.8% and 44.4% of forecast error variance can be attributed to return and volatility spillovers, highlighting low levels of connectedness among the stock markets. Additionally, the authors find Egypt, Mauritius, and South Africa to be the only net transmitters of return spillovers while South Africa is the only net transmitter of volatility spillovers. Furthermore, in their dynamic analysis, similar to Sugimoto et al. (2014) the authors find peaks of spillovers during the 2007-2009 Global Financial Crisis, the second and third quarters of 2015 during the oil price crash, 2016 during Brexit, and 2019 during the US-China trade wars.

Additionally, Antonakakis et al. (2023) explore dynamic connectedness, adopting the TVP-VAR connectedness approach with daily data, an extension of Diebold & Yilmaz's (2012) connectedness approach. The authors examine volatility connectedness among five asset classes (energy commodities, stock markets, precious metals, exchange rates and bond markets) between March 16th, 2011, to March 3rd, 2021.

In conclusion, the literature on connectedness in African financial markets reveals a complex landscape of integration, volatility dynamics, and spillover effects. While African stock markets present promising investment opportunities, the increased interconnectedness with global financial markets introduces new challenges. Understanding the role of different markets, both as transmitters and receivers of return and volatility spillovers, is essential for policymakers, investors, and researchers seeking to navigate and comprehend the evolving dynamics of financial markets in the African context. Further research is necessary to achieve market resilience, develop regulatory reforms, and attain long-term sustainability of financial integration in the African region.

This study will extend the existing literature by specifically providing evidence of financial connectedness among African stock markets beyond the 2007-2009 Global Financial Crisis, extending the dataset of Atenga & Mougoue (2021). Additionally, this study will adopt an aggregation method to analyse the full sample connectedness table.

3 Stylised Facts on Stock Market Development in Africa

Table 1: Stock Market Indicators: Market capitalisation, Market liquidity, Turnover Ratio, Listed Domestic Companies

Countries	Market Capitalisation				Market Liquidity		Turnover Ratio		Listed Domestic Companies	
	$millions		% of GDP		Value traded (% of GDP)		Value traded (% of market capitalisation)		Number	
	2010	2020	2010	2020	2010	2020	2010	2020	2010	2020
North Africa										
Egypt	84,277	41,351	38.48	11.32	16.99	4.40	44.2	38.9	227	220
Morocco	69,152	65,415	74.18	54.03	6.54	2.97	8.8	5.5	73	75
Tunisia	10,658	8,571	23.05	20.15	3.97	-	17.2	-	56	80
South Africa										
Botswana	67.5	3,561.16	17.6	-	0.7	-	3.5	-	31	32
South Africa	981.44	1,051,528,63	221.63	311.45	66.42	87.03	2.77	2.9	352	264
West Africa										
Nigeria	50,546	56,569	13.77	13.08	1.39	0.57	10.1	4.4	215	177
Ghana	29,477	92,474	9.16	13.20	0.32	0.05	3.45	0.35	31	31
Bvrm		8,100.13								47
East Africa										
Kenya	14,461	21,398	31.84	21.25	1.74	0.48	5.5	2.3	55	60
Mauritius	77,528	61,596	77.49	-	3.65	2.73	4.71	4.05	-	93

Advanced Economies										
United States	17,283,452	40,719,661	114.85	193.35	239.39	-	208.43	-	4279	-
United Kingdom	1,868,153		107.85		128.97		119.59		2105	
France	1,911,515		72.26		51.04		70.63		617	
Japan	3,827,774	6,718,219	66.47	133.07	74.15	125.52	111.56	94.33	2281	3754
Germany	1,429,719	2,284,108	42.05	58.72	43.96	46.64	104.54	79.42	690	438
Emerging Economies										
Brazil	1,545,565	9,883,743	69.97	66.96	41.11	93.05	58.76		373	345
China	4,027,840	12,214,465	66.17	83.16	135.66	215.01	205.02	258.55	2063	4154
Hong Kong	2,711,316	6,130,420	1185.85	1777.22	650.63	889.82	54.87	50.07	1396	2353
India	1,762,461	2,595,465	105.18	97.15	63.31	72.81	60.19	74.95	5034	5215
Russia	9,512,955	6,947,392	62.38	46.53	33.24	18.53	53.28	39.81	556	213

Source: World Development Indicators (accessed 22/06/23)

This section highlights stock market development in Africa between 2010 and 2020. Stock markets in Africa have developed quite rapidly in the last century which can be linked to financial sector reforms targeted at the development of capital markets across the region. Additionally, market capitalisation, the number of domestic companies listed, and trading volume have also seen an increase in the last decade. An interesting trend among African stock markets has been the development of a regional stock exchange – the Bourse régionale des Valeurs mobilieres (BRVM) situated in West Africa and serving French-speaking countries. Similar efforts are underway in South and East Africa in the consolidation of capitalised markets into regional markets. African Stock Market can be classified(aggregated) according to existing regions namely- Northern Africa, Southern Africa, Eastern Africa, and Western Africa.

Northern Africa

The Northern African stock market comprises of the stock markets of Egypt, Algeria, Libya, Morocco, Sudan, and Tunisia. This region is home to one of the oldest stock markets in Africa - the Egyptian Stock Market. The development of the stock market in this region varies from highly developed to small development. The Khartoum Stock Exchange of Sudan and the Algerian Stock Exchange are very small, with a market capitalisation of $139 million and $371 million respectively, as of 2018 (World Bank Database, 2022). The Egyptian Stock Exchange, Tunisian Stock Exchange and Morocco Stock Exchange are larger, with a total market capitalisation of $41 billion, $8.5 billion, and $58.7 billion respectively (World Bank Database, 2022). Additionally, the stock exchanges of Algeria and Sudan have fewer companies listed, highlighting that the stock exchange currently occupies a small role in raising capital for firms and the government.

The Egyptian Stock Exchange, also referred to as the Cairo and Alexandria Stock Exchange (CASE), is one of the oldest stock exchanges in Africa and the world. The CASE has experienced a drop in firms listed in recent years as seen in Table 1, with listed firms falling from 227 firms in 2010 to 220 in 2020.

Despite that the CASE stock exchange was established in the 18th century, it has lagged behind other stock exchanges within the region in development due to a lack of depth[5] in the market, which has limited corporate financing and business development. Additionally, the inability to raise equity capital has limited the development of the private sector in CASE.

Generally, political risk and weak economic prospects play a major role in influencing the stock prices in North Africa. The political instability in Egypt has affected the country's stock

[5] Limited supply and demand of liquid, tradeable assets. Additionally, domestic investors are risk averse, opting for saver investment options such as real-estate and interest-bearing bank deposits (OECD, 1994)

exchange, causing it to lose some of its major company listings. Specifically, the fall of the autocratic rule of Hosni Mubarak led to a decline in foreign investors.

Despite the challenges, stock markets in the Northern Africa region have regardless experienced increased integration with the global stock market. With increased integration, stock markets in Northern Africa have been exposed to the spread of systemic risk. Particularly, the Egyptian stock market was greatly affected by the 2007-2009 Global Financial Crisis, with a fall in total market capitalisation by 38.3% (Allen, 2011). Similarly, total market capitalisation fell in the Moroccan Stock Exchange by 13.5%. The response of the Egyptian Government was to use the shock to the stock market as a catalyst for privatising several companies that experienced a decline in their market indicators. Similar efforts were adopted by the Tunisian and Moroccan Stock exchange privatising companies which performed poorly.

Western Africa

WEAMU/French-Speaking Region

The Bourse régionale des Valeurs mobilieres (BRVM), the only regional stock exchange in Africa, serves the eight West African Monetary Union members. The BVRM is headquartered in Abidjan and has numerous branches located in the capital cities of the union's member

nations. Operations began in September 1998 with start-up capital assets totalling close to CFAF 2.9 billion, distributed among brokerage companies, chambers of commerce, subregional institutions, and private individuals. The exchange is responsible for the listing of securities, securities quotations, publication of market prices, and development of the securities exchange. Amid these duties, its primary function centres on aggregating and processing stock market orders sent by brokerage firms listed on the BRVM.

Additionally, securities are cleared by the Depositaire Central Bank de Reglement (DC/BC), which guarantees the settlement of each transaction and provides for default through a unique guaranteed fund. There are 46 companies listed on the BVRM as of 2023 (World Federation of Exchanges, 2024), with a market capitalization of FCFA 6,294,908.20, or $9756.37 at the current FCFA/USD exchange rate of 645.21 (African markets, accessed 03/08/22).

Through financial liberalisation and privatisation, the stock market has experienced growth. The region's secondary market is, however. underdeveloped. The derivatives industry is still developing, and there are some foreign exchange forwards with maturities of three to six months.

Non-WEAMU/English Speaking Region

The Non-Weamu's stock markets are at various levels of development and comprise of stock markets in individual countries of Nigeria, Ghana, Sierra Leone, Gambia, and Liberia. Gambia is in the process of setting up a capital market, and banks have been asked, formally, to list a given percentage of their shares in the new capital market. Consequently, only a few local entities are traded over the counter. Likewise, there is currently no stock exchange in Sierra Leone. However, a technical committee for the Sierra Leone Stock Exchange has been established to provide a framework for the country's potential future capital market.

The Ghana Stock Exchange became operational in 1990. As of 2009, there were 31 listed companies, which had a market capitalisation of $14.54 billion. It currently has 39 listed firms with a market capitalisation of $7.25 billion (Ghana Stock Exchange, 2022).

The Nigerian Stock Exchange was founded as the Lagos Stock Exchange in 1960 and has since expanded to 8 branches located throughout key cities. Government stocks, corporate shares, and industrial loans are among the listed securities. There are now 173 firms listed, with a market value of NGN 27.31 trillion (World Federation of Exchanges, 2022; African'xchanges, 2022).

The Nigerian and Ghanaian stock exchanges in the English-speaking region of Western Africa are in the process of harmonisation to establish uniform rules, regulations, and operational procedures to allow investors access to these markets freely.

Southern Africa

The Southern African Stock Exchange comprises the Botswana Stock Exchange, the Namibian Stock Exchange, the Johannesburg Stock Exchange, the Seychelles Stock Exchange, the Swaziland Stock Exchange, the Zambia Stock Exchange, and the Zimbabwe Stock Exchange. The largest stock exchange in Southern Africa is the Johannesburg Stock Exchange, which is Africa's first and most advanced stock exchange. It has been in operation for nearly 120 years, evolving from traditional type floor-based equities trading to a fully electronic modern exchange for trading, clearing, and settling securities, financial instruments, and other associated instruments. The total market capitalisation for the Johannesburg Stock Exchange is over $900 billion, with a listing of 322 companies (Johannesburg Stock Exchange, 2023).

Eastern Africa

The Eastern African stock exchange is not as developed as that of Southern, Western, or Northern Africa. Few countries in Eastern Africa have well-established stock markets with the Kenyan stock market taking the lead in the Eastern Africa region. Rwanda, Uganda, and Tanzania are the other stock exchanges which exist in the region.

The Nairobi Stock Exchange of Kenya was established in 1954 and is the oldest and most well-established stock exchange in the East & Central African Region. In terms of traded volume, it is the 4th largest stock exchange in Africa and the 5th largest in terms of market capitalisation.

The Nairobi stock exchange has a total market capitalisation of $25.1 million and a total of 61 listed companies(Nairobi Securities Exchange, 2023).

The stock exchange of Rwanda was established in 2008 as an over-the-counter market (OTC). As a young stock exchange, it has gained momentum over the years with a total market capitalization of $3.56 billion (World Federation of Exchanges, 2023).

Overall, the African stock markets are at various stages of development. From Table 1, we can see a common trend of growth among African stock markets from 2010 to 2020 in market capitalisation, market liquidity, turnover ratio and domestic firms listed. This has made African stock markets more attractive to foreign investors.

4. Data

The data set employed in this study is comprised of daily stock price indices denominated in local currencies for the ten largest African stock markets in 2020 by market capitalisation. We adopt this strategy for selecting African stock markets to give a true representation of stock markets, particularly so that large African stock markets are not excluded South Africa, Morocco, Nigeria, Egypt, Botswana, Kenya, Ghana, Tunisia, Mauritius and BVRM). Similarly, we select the five largest Advanced stock markets (UK, US, France, Germany, and Japan) and the five largest Emerging stock markets (Brazil, Hong Kong, Mexico, Russia, and China). Advanced and emerging stock markets are also selected based on foreign direct investment as the selection of African stock markets receive the most FDI's from the selected advanced and Emerging stock markets(see Appendix 3). The data frequency is daily, and the sample period is between January 3rd, 2011 and August 9th, 2023. All stock price indices were retrieved from the Bloomberg database.

Table 2: Descriptive Statistics of Stock Market Returns

	Min	Max	Std.Dev	Mean	Median	Skewness	Kurtosis
African Markets							
BOT	-4.07	2.01	0.22	0.01	0.00	-2.52	55.69
BVRM	-5.79	3.54	0.72	0.01	0.00	0.05	4.98
EGY	-10.52	7.59	1.37	0.04	0.00	-0.43	6.02
GHA	-5.80	5.18	0.70	0.04	0.00	0.56	12.40
MAU	-9.61	10.81	0.52	0.00	0.00	-1.06	128.86
MOR	-8.82	5.45	0.67	0.00	0.00	-1.02	18.04
NIG	-4.92	8.30	0.93	0.03	0.00	0.51	6.48
KEN	-6.75	8.88	1.09	0.02	0.00	-0.15	5.17
SA	-9.72	7.53	1.06	0.03	0.01	-0.42	6.57
TUN	-4.10	4.19	0.48	0.02	0.00	-0.83	14.03
Advanced Markets							
FRA	-12.28	8.39	1.25	0.03	0.04	-0.44	7.26
GER	-12.24	10.98	1.26	0.03	0.05	-0.31	7.42
USA	-11.98	9.38	1.09	0.04	0.03	-0.52	13.62
UK	-10.87	9.05	1.00	0.01	0.02	-0.56	9.67

JAP	-16.08	9.30	1.28	0.04	0.00	-0.66	13.41
Emerging Market							
BRA	-14.78	13.91	1.51	0.03	0.00	-0.52	10.81
HK	-6.36	9.08	1.25	0.00	0.00	0.09	3.82
RUS	-33.28	20.04	1.45	0.03	0.00	-3.49	99.97
IND	-12.98	8.76	1.05	0.04	0.01	-0.74	13.17
CHN	-8.49	5.76	1.23	0.01	0.00	-0.81	7.00

Source: Author's Calculation

Table 4 reports descriptive statistics of daily stock market returns. The standard deviation ranges from 0.22 to 1.37 for African stock markets, 1.00 to 1.28 for stock markets in advanced markets, and 0.96 to 1.51 for stock markets in emerging markets.

We also observe patterns in the distribution of returns from the skewness and kurtosis. The skewness measures are greater than 0 for all stock markets considered which suggests an asymmetric error in the distribution of stock market returns. Also, stock market returns are mostly negatively skewed in all markets except BVRM, Ghana, Nigeria, and Hong Kong. The kurtosis values are relatively high and statistically significant.

Furthermore, we adopt the E-Garch model as it accounts for the asymmetry in the impact of shocks on volatility through a leverage effect term. The leverage effect of the E- Garch model allows positive and negative shocks to have different effects on volatility, which is particularly useful when the data shows significant skewness. Additionally, E-Garch models are more flexible in terms of distributional assumptions of the residuals. E-Garch models can be paired with heavier-tailed distributions like the student's t-distribution, which better accommodate high kurtosis, capturing the leptokurtic nature of financial data.

4.1 VAR specification

A lag order of two is selected for all variables based on minimising the Akaike and Swartz's

Bayesian Information Criteria (AIC & BIC). This number of lags is used in the study by Diebold & Yilmaz (2009) which uses weekly data and Sugimoto et al. (2014) which uses daily data. For the rolling estimates, a 250 rolling window size is adopted like Atenga & Mougoue (2021). The forecast horizon (H) of 10 days is used, as seen in Diebold & Yilmaz (2009, 2012, 2014).

5. Methodology

This section outlines the EGARCH(1,1) model used to estimate time-varying conditional volatility series as an input into the analysis of spillovers (in addition to the analysis of spillovers in returns), the methodological framework used to compute spillover indices and the methodology used to calculate the aggregated results.

5.1. EGARCH modelling for time-varying volatility.

We estimate an EGARCH (1,1) model proposed by Nelson (1991) to generate daily volatilities. This model is adopted to generate volatilities for African data as it has the strength of capturing asymmetric effects among positive and negative asset returns. The model structure is detailed as follows:

$$r_t = \varepsilon + a_t \qquad \text{(Equation 10)[6]}$$

$$\ln \sigma_t^{\,2} = \alpha_0 + \sum_{i=1}^{p} a_i(|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}) + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2 \qquad \text{(Equation 11)}$$

where r_t is the returns series at time t and

$\varepsilon$is the mean of the GARCH model

α_t is the model's residual at time t

σ_t is the conditional standard deviation (i.e returns/volatility) at time

t p is the order of the ARCH co8mponent model

[6] Both equation 10 & 11 are estimated using a maximum likelihood estimator.

α_0 , α_1 α_2 , ….. α_p are the parameters of the ARCH component model q

is the order of the GARCH component model

β_j, β_j, β_j,………… β_q are the estimated parameters of the GARCH component model

ε_t are the residuals.

5.2 Model-based Analysis for Measuring Spillovers

This paper employs Diebold & Yilmaz's (2012, 2014) generalised variance decomposition approach to measure stock market return and volatility spillovers. This approach is built on the generalized VAR framework of Koop et al. (1996) and Pesaran & Shin (1998). It calculates the decompositions of the H-step ahead forecast error variance for each of the N variables of an N-dimensional Vector Autoregression (VAR) model. We can therefore examine the proportion of the forecast error variance of one variable(i) that can be attributed to shocks in another variable(j)[7]. The aggregation of these measures is then used to construct spillover indices. D & Y (2014) methodology allow variance decomposition to be examined as networks. Furthermore, the connectedness table and associated connectedness measures is a network adjacency matrix, allowing net connectedness measures to be used in conjunction with variance decomposition.

We assume the following VAR model for x_t:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \qquad \text{(Equation 1)}$$

[7] i= 1,2…..N
j= 1,2…….N

Where:

x_t = a vector of stock return or return volatilities

ε_t= a vector of independently distributed disturbances (or an error vector)

$\Phi_{i=}$ an N x N coefficient matrices

The moving average representation of the VAR model can be written as:

$$x_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-i} \qquad \text{(Equation 2)}$$

Where A_i is the N x N moving average coefficient matrix.

We make use of variance decomposition which allows us to analyse the forecast error variance of each variable into parts that are attributed to various system shocks. The variance decomposition allows us to examine the portion of the H-step ahead error variance in forecasting x_i that is due to shocks to x_j. We therefore define the H-step ahead generalised forecast error variance (Δ^{g}_{ij} (H)) as:

$$\Theta_{ij}{}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_i)}{\sum_{h=0} (e_i' A_h \, \Sigma A' \, h \, e_i)_{H-1}}$$
(Equation 3)

Where:

Σ is the variance matrix for the error vector σ_{ii} is the standard deviation

of the error term for the jth equation e_i is the selection vector with one

as the ith element and zeros otherwise.

Since the sum of the elements of each row of the variance decomposition table is not equal to 1, we normalise each entry of the variance decomposition matrix by the row sum as:

$$\theta^{g}_{ij}(H) = \frac{\theta^{g}_{ij}(H)}{\sum_{j=1}^{N} \theta^{g}_{ij}(H)} \qquad \text{(Equation 4)}$$

The total spillover index is created using the normalised components of equation 4. This measures the percentage of the variance in the H-step-ahead forecast error explained by shocks across all variables. The total spillover index is computed as:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \theta^{g}_{ij}(H)}{\sum_{i,j=1}^{N} \theta^{g}_{ij}(H)} \times 100 = \frac{1}{N} \sum_{\substack{i,j=1 \\ i\neq j}}^{N} \theta^{g}_{ij}(H) \times 100 \qquad \text{(Equation 5)}$$

We can now determine the direction of spillover effects coming from and going towards a specific equity market using the total spillover index. The generalised VAR framework facilitates the calculation of the directional spillover indices, which measure the spillovers that one market i receives from other markets j:

$$S^{g}_{i\cdot}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \theta^{g}_{ij}(H)}{\sum_{i,j=1}^{N} \theta^{g}_{ij}(H)} \times 100 \qquad \text{(Equation 6)}$$

The corresponding directional spillover index which measures the spillover effects transmitted by market *i* to all other equity markets *j* is represented below:

$$S^{g}_{\cdot i}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \theta^{g}_{ji}(H)}{\sum_{i,j=1}^{N} \theta^{g}_{ji}(H)} \times 100 \qquad \text{(Equation 7)}$$

Equations (6) and (7) allow us to calculate the net spillover index for market *i.* This measures the role played by *i* in the global system, that is, questioning if market *I* a leader or follower (receiver or transmitter of spillovers) is. It provides information on how much in net terms each equity market contributes to return/volatility variance in other equity markets. It is simply the difference between the net volatility shocks transmitted to and those received from all other markets. This is defined as:

$$S_{\cdot}^{g}{}_{i}(H) = S_{\cdot}^{g}{}_{i}(H) - S_{\cdot}^{g}{}_{i}(H) \quad \text{(Equation 8)}$$

Lastly, the net pairwise spillover is measured in equation (*9*), and this is the difference between gross spillovers transmitted from market *i to j* and gross spillovers transmitted from market *j to i.* This is defined as:

$$S_{ij}^{g}(H) = \left(\frac{\Theta^{g}{}_{ji}(H)}{\sum_{i,k=1}^{N} \Theta_{ik}^{g}(H)} - \frac{\Theta^{g}{}_{ij}(H)}{\sum_{j,k=1}^{N} \Theta_{jk}^{g}(H)}\right) \times 100 \quad \text{(Equation 9)}$$

A template of a connectedness table is included below:

Table 3: Sample Connectedness Table(Matrix)

	NIGERIA	BVRM	US	CHINA	From (FO)	Others
NIGERIA	d_{11H}	d_{12H}	d_{13H}	d_{14H}	$\sum_{j=1}^{N} d_{1j}^{H}, j \neq 1$	
BVRM	d_{21H}	d_{22H}	d_{23H}	d_{24H}	$\sum_{j=1}^{N} d_{2j}^{H}, j \neq 2$	
US	d_{31H}	d_{32H}	d_{33H}	d_{34H}	$\sum_{j=1}^{N} d_{3j}^{H}, j \neq 3$	
CHINA	d_{41H}	d_{42H}	d_{43H}	d_{44H}	$\sum_{j=1}^{N} d_{4j}^{H}, j \neq 4$	
TO OTHERS(TO)	$\sum_{i=1}^{N} d_{i1}^{H}$ $i \neq 1$	$\sum_{i=1}^{N} d_{i2}^{H}$ $i \neq 2$	$\sum_{i=1}^{N} d_{i3}^{H}$ $i \neq 3$	$\sum_{i=1}^{N} d_{i4}^{H}$ $i \neq 4$	$\frac{1}{N} \sum_{i,j=1}^{N} d_{ijH}$ $i \neq j$	

Source: Author's calculation

Table 2 contains 12 off-diagonal entries in the upper left 4 x 4 matrix with 12 pieces of the N(4) forecast error variance decomposition (d_{ij}). From a connectedness perspective, each entry measures the pairwise directional connectedness. The pairwise directional connectedness can be represented as:

$$C_{iH\leftarrow j} = d_{ijH}$$

We therefore have N^2- N individual pairwise directional connectedness measures[8].

We can also examine the net pairwise directional connectedness. This can be represented with

$$C_{iHj} = C_{jH\leftarrow i} - C_{iH\leftarrow j}$$

We have $\frac{N^2-N}{2}$ net pairwise directional connectedness measures.

The 8 off-diagonal row and column sums labelled as "FROM OTHERS" and "TO OTHERS" in Table 2 are the total directional connectedness measures. The FO_2 entry represents the fraction of variation BVRM receives from others (Nigeria, the US, and China). The total directional connectedness from others to i can be represented as:

$$C_{iH\leftarrow\cdot} = \sum_{\substack{j=1 \\ j\neq i}}^{N} d_{ijH}$$

And the total directional connectedness from j to others is:

$$C_{\cdot H\leftarrow j} = \sum_{\substack{i=1 \\ i\neq j}}^{N} d_{ijH}$$

We have 2N total directional connectedness measures.

We can also examine the net directional connectedness measure. This is represented as:

[8] N= 4 because we have a 4-dimensional matrix (4 countries) in the sample table
D is the off-diagonal elements while C defines the various measures of connectedness

$$C_{iH} = C_{.H\leftarrow i} - C_{iH\leftarrow .}$$

There are N net total directional connectedness measures.

Lastly, the grand total of the off-diagonal entries measures total system-wide connectedness. This is expressed as the cross-variable variance contribution as a percentage of total variation, given as TSI (Total spillover index) in Table 2. This is represented as:

$$C_H = \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} d_{ijH}$$

Table 4: Sample Aggregated Table

	Other African	**Advanced**	**Emerging**	**From Others (FO)**
NIGERIA	B11	B12	B13	SUMB2:B4)
BVRM	B21	B22	B23	SUM(C2:C4)
AFRICAN	**SUM(B2:B3)**	**SUM(C2:C3)**	**SUM(C2:3)**	**SUM(D2:D4)**
US	B31	B32	B33	SUM(E2:E4)
ADVANCED	**=B31**	**=B32**	**=B33**	**SUM(F2:F4)**
CHINA	B41	B42	B43	SUM(G2:G4)
EMERGING	**=B41**	**=B42**	**=B43**	**SUM(H2:H4)**

Source: Author's calculation

Table 3 sets out a template for the aggregation analysis. Novel to the existing literature, we aggregate stock markets into other

African, Advanced, and Emerging. Within Africa, we aggregate stock markets into West Africa, North Africa, South Africa, and East Africa as seen in Tables 5 & 6.

6.0 Empirical Results and Discussion

This study empirically examines spillovers across ten African stock markets, five advanced and five emerging stock markets by adopting Diebold & Yilmaz's (2012, 2014) methodology to daily data between January 3rd, 2011 - August 9th, 2023. We analyse connectedness beyond past crises to include the COVID-19 pandemic. We present our full sample results, aggregated results and rolling sample results in this section. The empirical estimates of spillover indices as well as their aggregates are reported in Tables 5, 6 & 7.

6.1 Full Sample Results

The empirical results presented in this study confirm the findings of previous studies, despite some differences in the country, setting and period analysed. Our findings show that global effects dominate regional effects among the largest African stock markets as Tables 5 & 6 highlight greater return and volatility spillovers from stock markets in advanced & emerging market economies to the stock markets of Nigeria, South Africa, Mauritius, Egypt, and Morocco. Our findings are similar to Sugimoto et al. (2014) and Atenga & Mougoue (2021) who also find little to no regional effect among African stock markets. Specifically, we find i) low levels of connectedness between African stock markets and stock markets in advanced and emerging market economies, except for South Africa, Mauritius, and Egypt (the total spillover index highlights that 35% and 45% of the forecast error variance can be attributed to return and volatility spillovers. On the other hand, Atenga & Mougoue (2021) and Sugimoto et al. (2014) total spillover index highlights that 40% and 50% of return and volatility spillover can be attributed to return and volatility spillovers.[i]. ii) Global effects are most prominent in the stock markets of South Africa and Egypt as international connectedness accounts for 76% & 69% and 24% & 28% for return and volatility respectively. Atenga & Mougoue (2021) and

Sugimoto et al. (2014) find international connectedness of South Africa and Egypt to account for 72% & 65% and 36% & 50% for return and volatility respectively. Global effects are least prominent in the stock markets of Botswana and BVRM as international connectedness accounts for 2.24% & 2.23% and 2.36% & 2.08% for return and volatility respectively. This supports Atenga & Mougoue's (2021) finding of international connectedness of less than 5% in BVRM and Botswana. iii) Furthermore, we find that most African stock markets are net receivers of return and volatility spillovers except for South Africa, Kenya and BVRM which are net transmitters of return and volatility spillovers as seen in Table 7. This contrasts the findings of Atenga & Mougoue (2021) who find South Africa and Nigeria as the only net transmitters of return and volatility spillovers, excluding Kenya in their study despite it being a highly capitalised African stock market.

Table 5: Total Directional Return & Volatility Connectedness FROM Other African, Advanced and Emerging Market Economies to Individual African Stock Markets.

	Returns				*Volatilities*			
	Other African	**Advanced**	**Emerging**	**Total FROM**	**Other African**	**Advanced**	**Emerging**	**Total FROM**
BVRM	1.36	0.63	0.38	2.37	1.24	0.15	0.69	2.08
GHA	1.38	0.52	0.48	2.38	2.63	0.4	1.35	4.38
NIG	3.59	3.07	5.63	12.29	4.25	7.54	1.91	13.7
WA	**6.33**	**4.22**	**6.49**	**17.04**	**8.12**	**8.09**	**3.95**	**20.16**
SA	1.9	25.02	41.63	68.55	2.05	56.57	17.15	75.77
BOT	0.95	0.6	0.71	2.26	1.04	0.44	0.74	2.22
SA	**2.85**	**25.62**	**42.34**	**70.81**	**3.09**	**57.01**	**17.89**	**77.99**
KEN	4.73	1.58	4.43	10.74	4.44	10.47	5.87	20.78
MAU	6.44	6.4	10.38	23.22	3.83	6.56	5.18	15.57
EA	**11.17**	**7.98**	**14.81**	**33.96**	**8.27**	**17.03**	**11.05**	**36.35**
EGY	5.28	6.86	11.47	23.61	4.31	17.26	5.94	27.51
MOR	4.94	4.64	6.23	15.81	7.92	20.16	12.15	40.23
TUN	2.4	1.18	0.89	4.47	6.39	4.86	2.86	14.11
NA	**12.62**	**12.68**	**18.59**	**43.89**	**18.62**	**42.28**	**20.95**	**81.85**

Source: Author's Calculation

Table 6: Total Directional Return & Volatility Connectedness TO Other African, Advanced and Emerging Market Economies from Individual African Stock Markets.

	Returns				*Volatilities*			
	Other African	**Advanced**	**Emerging**	**Total TO**	**Other African**	**Advanced**	**Emerging**	**Total TO**
BVRM	0.64	0.51	0.23	1.38	2.13	0.47	0.13	2.73
GHA	0.77	0.54	0.19	1.5	2.23	0.03	0.51	2.77
NIG	3.12	1.17	0.62	4.91	1.75	0.24	0.4	2.39
WA	**4.53**	**2.22**	**1.04**	**7.79**	**6.11**	**0.74**	**1.04**	**7.89**
SA	8.8	20.68	43.72	73.2	11.18	38.55	30.55	80.28
BOT	0.64	0.51	0.23	1.38	0.76	0.05	0.12	0.93
SA	**9.44**	**21.19**	**43.95**	**74.58**	**11.94**	**38.6**	**30.67**	**81.21**
KEN	4.1	14.99	0.58	19.67	5.69	1.63	1.86	9.18
MAU	3.9	1.65	0.41	5.96	1.12	0.38	0.32	1.82
EA	**8**	**16.64**	**0.99**	**25.63**	**6.81**	**2.01**	**2.18**	**11**
EGY	4.43	1.65	2.38	8.46	4.1	0.74	1.87	6.71
MOR	5.1	1.73	2.51	9.34	6.51	2.97	7.19	16.67
TUN	0.98	1.35	0.12	2.45	2.63	0.2	0.3	3.13
NA	**10.51**	**4.73**	**5.01**	**20.25**	**13.24**	**3.91**	**9.36**	**26.51**

Source: Authors Calculation

Table 7: Net Directional Return & Volatility Spillovers TO – FROM Other African, Advanced and Emerging Stock Markets.

	Returns				*Volatilities*			
	Other African	**Advanced**	**Emerging**	**Total NET**	**Other African**	**Advanced**	**Emerging**	**Total NET**
BVRM	-0.23	-0.32	-2.26	-2.81	0.89	0.32	-0.56	0.65
GHA	-0.61	0.02	-0.29	-0.88	-0.4	-0.37	-0.84	-1.61
NIG	-0.47	-1.9	-5.01	-7.38	-2.5	-7.3	-1.51	-11.31
WA	**-1.31**	**-2.2**	**-7.56**	**-11.07**	**-2.01**	**-7.35**	**-2.91**	**-12.27**
SA	6.9	-4.34	2.09	4.65	9.13	-18.02	13.4	4.51
BOT	-0.31	-0.09	-0.48	-0.88	-0.28	-0.39	-0.62	-1.29
SA	**6.59**	**-4.43**	**1.61**	**3.77**	**8.85**	**-18.41**	**12.78**	**3.22**
KEN	-0.63	13.41	-3.85	8.93	1.25	-8.84	-4.01	-11.6
MAU	-2.54	-4.75	-9.97	-17.26	-2.71	-6.18	-4.86	-13.75
EA	**-3.17**	**8.66**	**-13.82**	**-8.33**	**-1.46**	**-15.02**	**-8.87**	**-25.35**
EGY	-0.85	-5.21	-9.09	-15.15	-0.21	-16.52	-4.07	-20.8
MOR	0.16	-2.91	-3.72	-6.47	-1.41	-17.19	-4.96	-23.56
TUN	-1.42	0.17	-0.77	-2.02	-3.76	-4.66	-2.56	-10.98
NA	**-2.11**	**-7.95**	**-13.58**	**-23.64**	**-5.38**	**-38.37**	**-11.59**	**-55.34**

Source: Author's Calculation

6.2 Regional Aggregations

While the full system connectedness matrix provides insights into the nature of spillovers across stock markets included in this study, we adopt an aggregated spillover method to have a closer look at spillovers across regions. Again, we observe global effects dominating regional effects. Tables 5 & 6 highlight stock market regional aggregation within Africa and with the rest of the world[9]. Our findings reveal that: i) Regional effects dominate among the stock markets of Botswana, BVRM, Ghana, Kenya, and Tunisia as they receive and transmit the highest percentage of return and volatility spillovers to other African stock markets (as seen in table 5 & 6). ii) Global effects dominate among the stock markets of Egypt, Mauritius, Morocco, Nigeria, and South Africa as they receive the highest percentage of return and volatility spillovers from Advanced and Emerging market economies. iii) Botswana, BVRM, Ghana, Kenya, Mauritius, Morocco, Nigeria, and Tunisia are net receivers of return spillovers, implying that these stock markets receive more spillovers (shocks) from other stock markets(as seen in table 7). iv) BVRM and South Africa are net transmitters of volatility spillovers, implying that these stock markets transmit more spillovers than they are receiving from other stock markets.

Within Africa, we observe from table 7 that i) Regional effects dominate among stock markets in Northern Africa as they receive the largest return and volatility spillovers (12.62% & 18.62%) from other African stock markets. ii) Global effects dominate among stock markets in Southern Africa as they receive the highest percentage of return and volatility spillovers (42.34% & 57.01%) from stock markets in advanced and emerging economies.

[9] We aggregate countries into Advanced, Emerging, and African stock markets. Within Africa, we aggregate stock markets based on regions- North Africa, South Africa, East Africa, and West Africa.

6.3 Time-Varying Estimates

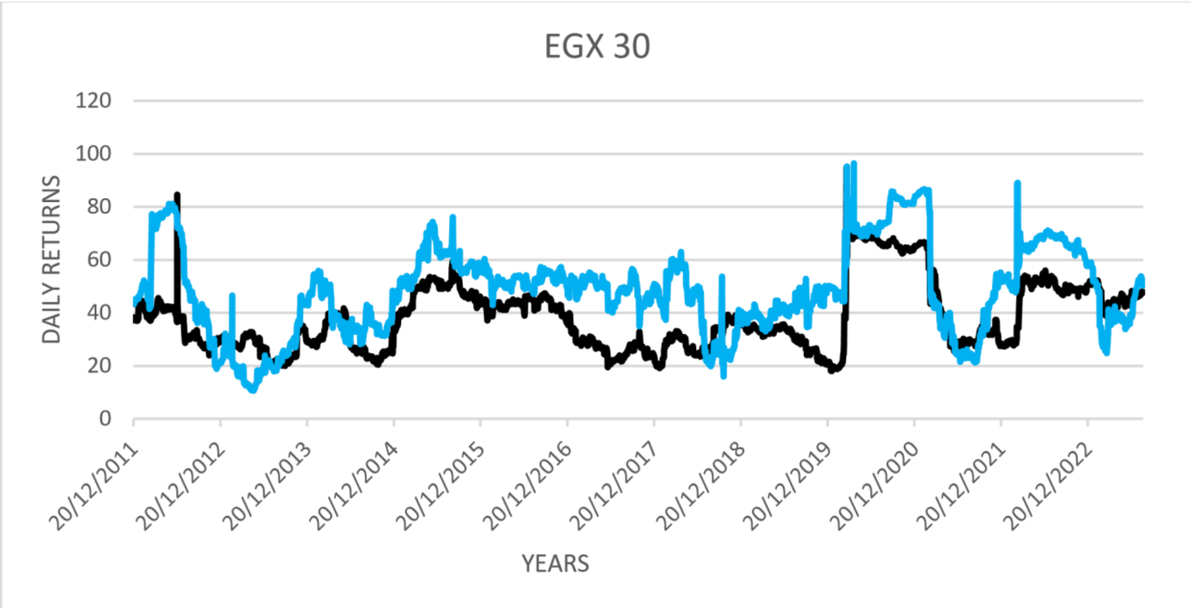
The time-varying analysis in Figure 3 explores how a measure of spillovers has evolved. We present the time-varying results for the two largest African stock markets, which display a similar pattern to other stock markets[10]. African stock markets have experienced significant growth over the last decade. Table 1 highlights key development indicators across African stock markets. In light of the growth of African stock markets, we explore rolling sample estimates before and during the COVID-19 crisis. Our results confirm previous findings (Atenga & Mougoue, 2021 and Sugimoto et al., 2014), also highlighting the dominance of global effects on African stock markets. We find that African stock markets had more pronounced spillovers during the 2012 European sovereign debt crisis, the commodity price crash of 2015, Brexit in 2016 and the US-China trade wars in 2019. Consistent with the literature, we also observe a few country-specific trends characterised by high spillovers i.e. The 2015 rise in oil prices in Nigeria, anti-government protests and political instability in North Africa, and currency depreciation in South Africa. New to existing evidence, we find more pronounced return and volatility spillovers during the COVID-19 pandemic between 2020-2022.

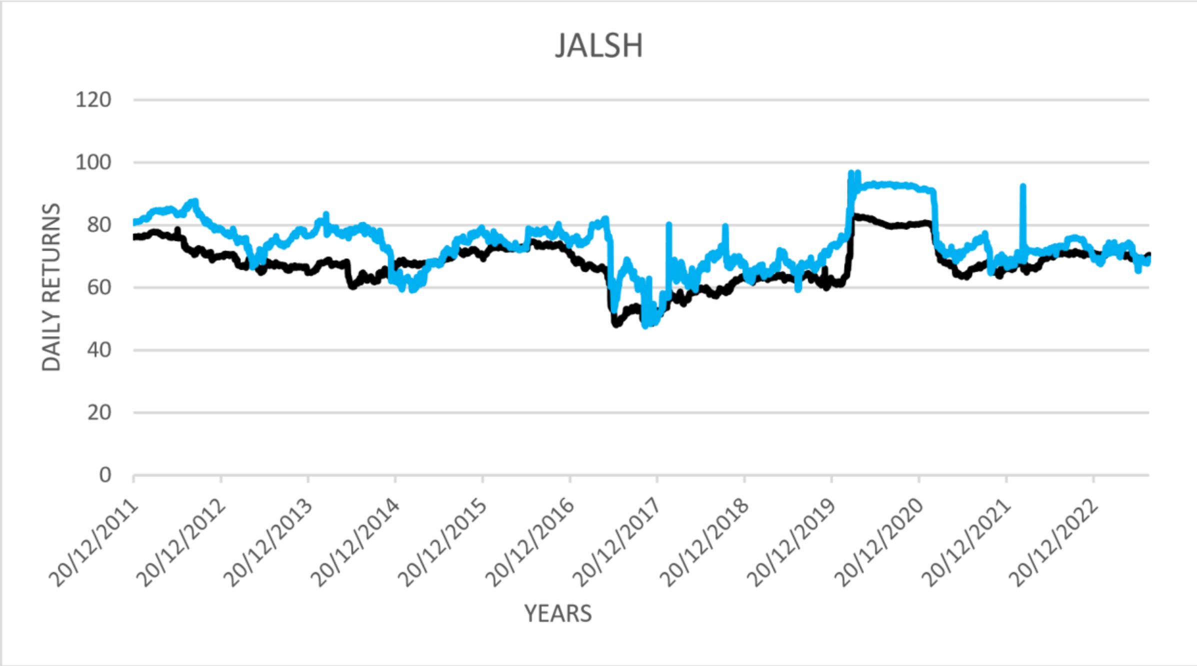
From Figure 3, we can observe that spillovers were greatest during the 2012 European sovereign debt crisis, the COVID-19 pandemic. We estimate the connectedness table for the pre-COVID-19 (European Sovereign Debt Crisis) and the COVID-19 period and then compare the total spillover index of return and volatility.

Similar to the full sample connectedness table, we also observe global effects dominating regional effects as African stock markets receive the most return and volatility spillovers form stock markets in advanced and emerging market economies.

[10] See Appendix for full results

The comparison of the total spillover index for both periods reveals that 49% of the forecast error variance can be attributed to return spillovers during the 2012 European Sovereign Debt Crisis while 41% of the forecast error variance can be attributed to spillovers in returns during the 2012 Sovereign Debt Crisis. On the other hand, 49% of the forecast error variance can be attributed to spillovers in volatility. In other words, 50% of shocks among African stock markets could be attributed to return spillovers during the 2012 Sovereign Debt Crisis while 53% of shocks to African stock markets can be explained by volatility spillovers during the COVID-19 pandemic.





Source: Author's calculation

Figure 3: Directional return and volatility spillovers to African equity markets from other equity markets. Note: The black line represents volatility spillovers, and the blue lines represent return spillovers.

7.0 Conclusion

The main aim of this study is to explore how connected African stock markets are within Africa and with the rest of the world. To achieve this, we adopt the Diebold and Yilmaz (2012, 2014) network methodology, exploring the full sample and rolling sample (time-varying) return and volatility estimates, focusing on the period after the Global Financial Crisis of 2007-2009. Additionally, we adopt an aggregation method, pairing countries into aggregated Africa, Advanced, and Emerging, as well as Northern Africa, Western Africa, Eastern Africa, and Southern Africa, to examine in greater detail the transmission of spillovers.

This study produces a few interesting results. Firstly, in our full sample results, we confirm previous findings as global effects dominate regional effects among African stock markets. Furthermore, South Africa is most impacted by global effects as international connectedness accounts for 76% and 69% of return and volatility spillovers. On the other hand, Botswana and BVRM are least impacted by global effects as international connectedness accounts for 2.24% & 2.23% and 2.36% & 2.08% of return and volatility spillovers respectively. Additionally, on average, African stock markets receive more return and volatility spillovers from other global stock markets than they transmit, with the exception of South Africa, Kenya and BVRM which are net transmitters of return and volatility spillovers.

Secondly, in our aggregated analysis, a few interesting trends arise. While global effects dominate on average among African stock markets, we observe that some regional effects dominate for Botswana, BVRM, Ghana, Kenya, and Tunisia, as these stock markets receive the highest percentage of return and volatility spillovers from other African stock markets. This highlights that these African stock markets are more connected with themselves (other African stock markets). On the other hand, global effects dominate in Egypt, Mauritius, Morocco, Nigeria, and South Africa as these stock markets receive the highest percentage of return and volatility spillovers from stock markets in Advanced and Emerging Market Economies.

Additionally, when we examine regional aggregation within Africa, we find that stock markets in North Africa receive the largest return and volatility spillovers (12.62% & 18.62%) from other African Stock markets while stock markets in South Africa receive the largest return and volatility spillovers (70.81% and 77.99%) from stock markets in Advanced and Emerging Economies.

In our rolling sample analysis, we observe peaks of spillovers appearing during the 2012 European Sovereign Debt Crisis, the commodity price crash of 2015, and Brexit in 2016 across each African stock market. We also observe a few country-specific trends characterised by high spillovers i.e. The 2015 rise in oil prices in Nigeria, anti-government protests and political instability in North Africa, and currency depreciation in South Africa New to existing evidence, we find pronounced spillovers during the Covid-19 Pandemic between 2020-2022.

The empirical result of this study is useful for investors, policymakers, and monetary authorities within Africa. For investors, the low levels of spillover among African stock markets provide an opportunity for hedging to investors within Africa and advanced and emerging market economies. For policy makers, the low levels of spillovers between African stock markets and global stock markets, highlights the need to create policies that will encourage foreign participation in African stock markets but also target financial stability. Lastly, the time varying findings of this study provides financial regulators and monetary authorities insights into how spillovers have spread in Africa over time, further equipping their policy development.

While beyond the scope of this paper, exploring the determinants of return and volatility spillovers within the African stock market provides scope for future research that could address current knowledge gaps. Additionally, including a larger sample of the African stock market will provide more insights into the transmission of spillovers among African stock markets.

References

ADRIAN, T. & BRUNNERMEIER, M. K. 2011. CoVaR. National Bureau of Economic Research.

ALLEN, F., OTCHERE, I. & SENBET, L. W. 2011. African financial systems: A review. *Review of Development Finance,* 1**,** 79-113.

ANDO, T., GREENWOOD-NIMMO, M. & SHIN, Y. 2022. Quantile connectedness: modeling tail behavior in the topology of financial networks. *Management Science,* 68**,** 2401-2431.

ANTONAKAKIS, N., CHATZIANTONIOU, I. & FILIS, G. 2017. Oil shocks and stock markets: Dynamic connectedness under the prism of recent geopolitical and economic unrest. *International Review of Financial Analysis,* 50**,** 1-26.

ANTONAKAKIS, N., CHATZIANTONIOU, I. & GABAUER, D. 2020. Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions. *Journal of Risk and Financial Management,* 13.

ANTONAKAKIS, N., CUNADO, J., FILIS, G., GABAUER, D. & DE GRACIA, F. P. 2023. Dynamic connectedness among the implied volatilities of oil prices and financial assets: New evidence of the COVID-19 pandemic. *International Review of Economics & Finance,* 83**,** 114-123.

ANTONAKAKIS, N. & KIZYS, R. 2015. Dynamic spillovers between commodity and currency markets. *International Review of Financial Analysis,* 41**,** 303-319.

AROURI, M. E. H., JOUINI, J. & NGUYEN, D. K. 2012. On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. *Energy Economics,* 34**,** 611-617.

ATENGA, E. M. E. & MOUGOUÉ, M. 2021. Return and volatility spillovers to African currencies markets. *Journal of International Financial Markets, Institutions and Money,* 73**,** 101348.

ATENGA, E. M. E. & MOUGOUÉ, M. 2021. Return and volatility spillovers to African equity markets and their determinants. *Empirical Economics,* 61**,** 883-918.

AWARTANI, B., AKTHAM, M. & CHERIF, G. 2016. The connectedness between crude oil and financial markets: Evidence from implied volatility indices. *Journal of Commodity Markets,* 4**,** 56-69.

BAELE, L. 2005. Volatility Spillover Effects in European Equity Markets. *Journal of Financial and Quantitative Analysis,* 40**,** 373-401.

BALCILAR, M., ELSAYED, A. H. & HAMMOUDEH, S. 2023. Financial connectedness and risk transmission among MENA countries: Evidence from connectedness network and clustering analysis1. *Journal of International Financial Markets, Institutions and Money,* 82**,** 101656.

BANK, W. 2023. World Bank Database. *In:* BANK, W. (ed.).

BARUNÍK, J., KOČENDA, E. & VÁCHA, L. 2017. Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance,* 77**,** 39-56.

BILLIO, M., GETMANSKY, M., LO, A. W. & PELIZZON, L. 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics,* 104**,** 535-559.

BOURI, E. 2015. Oil volatility shocks and the stock markets of oil-importing MENA economies: A tale from the financial crisis. *Energy Economics,* 51**,** 590-598.

CANOVA, F., CICCARELLI, M. & ORTEGA, E. 2007. Similarities and convergence in G-7 cycles. *Journal of Monetary economics,* 54**,** 850-878.

CHIEN, M. S., LEE, C. C., HU, T. C. & HU, H. T. 2015. Dynamic Asian stock market convergence: Evidence from dynamic cointegration analysis among China and ASEAN-5. *Economic Modelling,* 51**,** 84-98.

CLAESSENS, S. & FORBES, K. 2001. International financial contagion: An overview of the issues and the book. *International financial contagion***,** 3-17.

COSKUN, M., KHAN, N., SALEEM, A. & HAMMOUDEH, S. 2023. Spillover connectedness nexus geopolitical oil price risk, clean energy stocks, global stock, and commodity markets. *Journal of Cleaner Production,* 429**,** 139583.

DATA, F. R. E. 2024.

DIEBOLD, F. X. & YILMAZ, K. 2008. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal,* 119**,** 158-171.

DIEBOLD, F. X. & YILMAZ, K. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal,* 119**,** 158-171.

DIEBOLD, F. X. & YILMAZ, K. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting,* 28**,** 57-66.

DIEBOLD, F. X. & YILMAZ, K. 2015. Trans-Atlantic equity volatility connectedness: U.S. and European financial institutions, 2004-2014. *Journal of Financial Econometrics,* 14**,** 81-127.

DIEBOLD, F. X. & YILMAZ, K. 2023. On the past, present, and future of the Diebold–Yilmaz approach to dynamic network connectedness. *Journal of Econometrics,* 234**,** 115-120.

DIEBOLD, F. X. & YıLMAZ, K. 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics,* 182**,** 119-134.

DIEBOLD, F. X. & YıLMAZ, K. 2015. *Financial and macroeconomic connectedness: A network approach to measurement and monitoring*, Oxford University Press, USA.

EL GHINI, A. & SAIDI, Y. 2017. Return and volatility spillovers in the Moroccan stock market during the financial crisis. *Empirical Economics,* 52**,** 1481-1504.

ENGLE, R. 2009. *Anticipating correlations: a new paradigm for risk management*, Princeton University Press.

ENOCH, M. C., MATHIEU, M. P. H., MECAGNI, M. M. & KRILJENKO, M. J. I. C. 2015. Pan-African Banks: Opportunities and challenges for cross-border oversight.

EXCHANGE, J. S. 2023.

EXCHANGE, N. S. 2023.

EXCHANGES, W. F. O. 2023.

FORBES, K. J. & WARNOCK, F. E. 2012. Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of international economics,* 88**,** 235-251.

FOWOWE, B. & SHUAIBU, M. 2016. Dynamic spillovers between Nigerian, South African and international equity markets. *International Economics,* 148**,** 59-80.

GREENWOOD-NIMMO, M. & NGUYEN, V. H. 2015. Measuring the Connectedness of the Global Economy. Melbourne Institute of Applied Economic and Social Research, The University of Melbourne.

GREENWOOD-NIMMO, M., NGUYEN, V. H. & SHIN, Y. 2015. Measuring the connectedness of the global economy.

GREENWOOD-NIMMO, M., NGUYEN, V. H. & SHIN, Y. 2021. Measuring the Connectedness of the Global Economy. *International Journal of Forecasting,* 37**,** 899-919.

HABIBI, H. & MOHAMMADI, H. 2022. Return and volatility spillovers across the Western and MENA countries. *The North American Journal of Economics and Finance,* 60**,** 101642.

HAMILTON, J. D. 2020. *Time series analysis*, Princeton university press.

HASAN, M. B., MAHI, M., SARKER, T. & AMIN, M. R. 2021. Spillovers of the COVID-19 Pandemic: Impact on Global Economic Activity, the Stock Market, and the Energy Sector. *Journal of Risk and Financial Management,* 14**,** 200.

JAYASURIYA, S. A. 2011. Stock market correlations between China and its emerging market neighbors. *Emerging Markets Review,* 12**,** 418-431.

KANG, S. H., MAITRA, D., DASH, S. R. & BROOKS, R. 2019. Dynamic spillovers and connectedness between stock, commodities, bonds, and VIX markets. *Pacific Basin Finance Journal,* 58.

KIM, J.-M. & JUNG, H. 2018. Dependence Structure between Oil Prices, Exchange Rates, and Interest Rates. *The Energy Journal,* 39**,** 259-280.

KOOP, G., PESARAN, M. & POTTER, S. 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics,* 74**,** 119-147.

KOSE, M. A., PRASAD, E. S. & TERRONES, M. E. 2003. How does globalization affect the synchronization of business cycles? *American Economic Review,* 93**,** 57-62.

LÉON, F. & ZINS, A. 2020. Regional foreign banks and financial inclusion: Evidence from Africa. *Economic Modelling,* 84**,** 102-116.

MAGHYEREH, A. I. & AWARTANI, B. 2016. Dynamic transmissions between Sukuk and bond markets. *Research in International Business and Finance,* 38**,** 246-261.

MALIK, F. & UMAR, Z. 2019. Dynamic connectedness of oil price shocks and exchange rates. *Energy Economics,* 84**,** 104501.

MARKETS, A. 2022.

NELSON, D. B. 1991. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society***,** 347-370.

NESBITT, J. 2016. *Exponential General Autoregressive Conditional Heteroskedastic (EGARCH) Model* [Online]. Available: https://support.numxl.com/hc/en-us/articles/214502046-Exponential-General-Autoregressive-Conditional-Heteroskedastic-EGARCH-Model [Accessed 07/02/24 2024].

PARK, H. & SHIN, Y. 2014. Mapping Korea's international linkages using generalised connectedness measures. *Bank of Korea WP,* 16.

PESARAN, H. H. & SHIN, Y. 1998. Generalized impulse response analysis in linear multivariate models. *Economics letters,* 58**,** 17-29.

SHOJAIE, A. & MICHAILIDIS, G. 2010. Discovering graphical Granger causality using the truncating lasso penalty. *Bioinformatics,* 26**,** i517-i523.

SOUMARÉ, I., KANGA, D., TYSON, J. & RAGA, S. 2021. Capital market development in sub-Saharan Africa: Progress, challenges and innovations. *Joint FSD Africa and ODI working paper. London: Overseas Development Institute*.

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.

TAYLOR, S. J. 2011. *Asset price dynamics, volatility, and prediction,* Princeton university press.

TSAY, R. S. 2005. *Analysis of financial time series,* John wiley & sons.

WANG, Z., LI, Y. & HE, F. 2020. Asymmetric volatility spillovers between economic policy uncertainty and stock markets: Evidence from China. *Research in International Business and Finance,* 53**,** 101233.

World Bank Database (2023).

WU, F. 2020. Stock market integration in East and Southeast Asia: The role of global factors. *International Review of Financial Analysis,* 67**,** 101416.

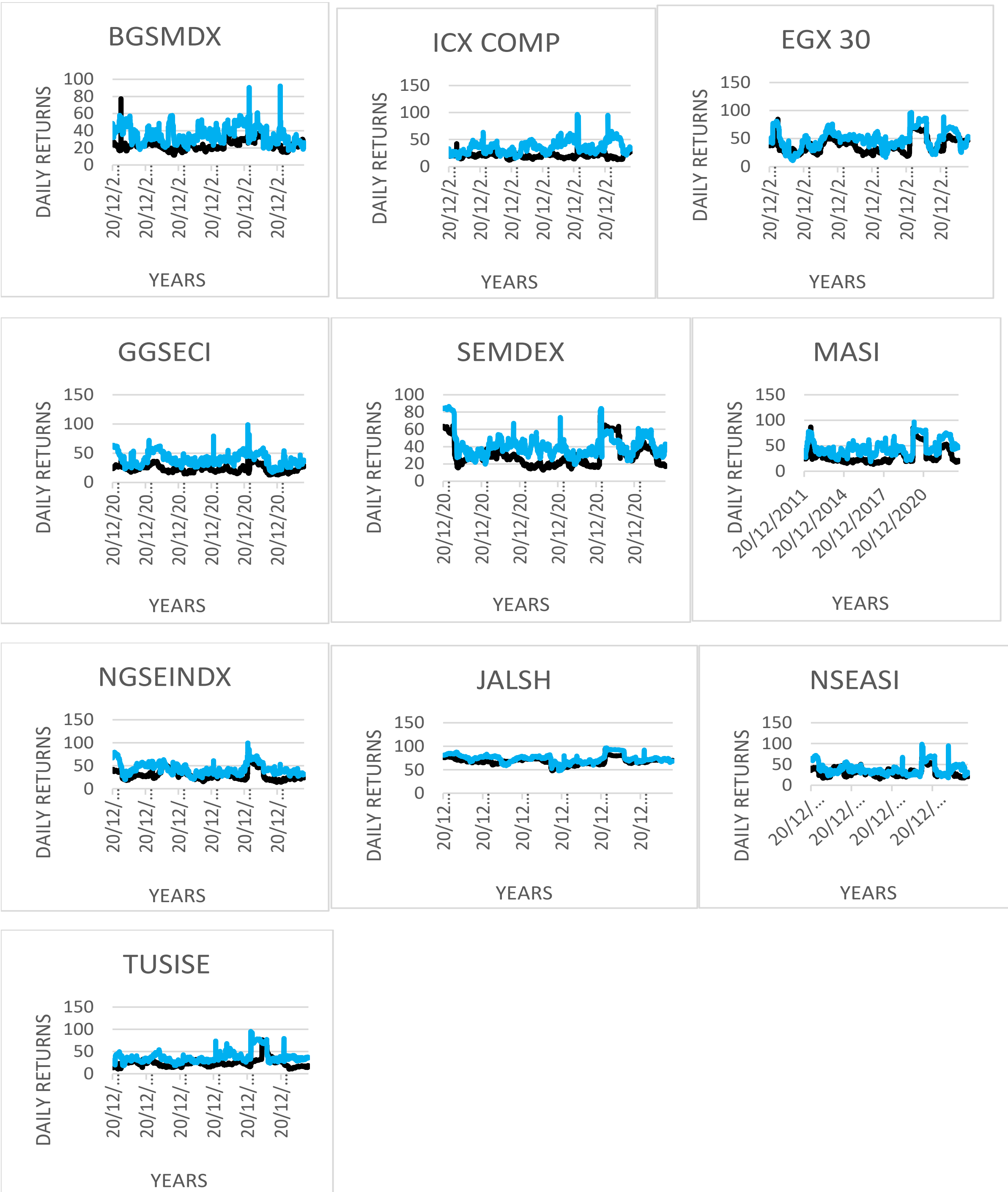
'XCHANGES, A. 2022.

ZHANG, H., CHEN, J. & SHAO, L. 2021. Dynamic spillovers between energy and stock markets and their implications in the context of COVID-19. *Int Rev Financ Anal,* 77**,** 101828.

Appendix

Appendix 1

Figure 3: Directional return and volatility spillovers to African equity markets from other equity markets. Note: The black line represents volatility spillovers, and the blue lines represent return spillovers.



Source: Author's calculation

Appendix 2

Returns Connectedness Table for Covid-19 Period

	FROM
BOT	13.98
BVRM	7.88
EGY	42.56
GHA	6.62
MAU	42.55
MOR	33.8
NIG	10.21
SA	71.29
KEN	11.5
TUN	12.05
FRA	20.3
GER	26.01
USA	5.07
UK	76.56
JAP	75.84
BRA	70.09
HK	74.9
RUS	62.61
IND	51.97
CHN	62.1
TO	777.91
INC.OWN	Inc.Own "cTCI/TCI"
NET	40.94/38.90
NPT	

Volatilities

	FROM
BOT	9.34
BVRM	11.95
EGY	64.89
GHA	5.34
MAU	22.60
MOR	70.03
NIG	11.74
SA	79.71
KEN	34.09
TUN	43.35
FRA	78.64

GER	78.43
USA	64.90
UK	76.99
JAP	55.77
BRA	66.39
HK	66.25
RUS	40.98
IND	81.78
CHN	34.84
TO	998.01
Own	cTCI/TCI
NET	52.53/49.90

European Sovereign Debt Crisis

Returns

	FROM
BOT	18.27
BVRM	21.06
EGY	27.81
GHA	19.71
MAU	51.24
MOR	22.11
NIG	30.75
SA	74.51
KEN	33.08
TUN	10.66
FRA	22.38
GER	34.78
USA	18.74
UK	79.18
JAP	79.07
BRA	77.62
HK	79.84
RUS	73.88
IND	79.70
CHN	74.44
TO	928.82
OWN	CTCI/TCI
NET	48.89 /46.44

Volatilities

	FROM
BOT	18.27
BVRM	21.06
EGY	27.81
GHA	19.71
MAU	51.24
MOR	22.11
NIG	30.75
SA	74.51
KEN	33.08
TUN	10.66

FRA	22.38
GER	34.78
USA	18.74
UK	79.18
JAP	79.07
BRA	77.62
HK	79.84
RUS	73.88
IND	79.70
CHN	74.44
TO	928.82
Own	cTCI/TCI
NET	48.89/46.44

Appendix 3

African Economies	**FDI(2020)**	**FDI(2021)**	**FDI(2022)**
BVRM	-	-	-
GHA	1875782953	2612789793	1510872058
NIG	2385277666	3313210000	-186792429
SA	3150000000	40660000000	9190000000
BOT	31792610.41	-319055858	216459291.1
KEN	426305189.4	463348935.7	393583092.1
MAU	224668083	253189253	252104280
EGY	5851800000	5122300000	11399900000
MOR	1418713119	2264148625	2177845609
TUN	623075275.9	547411353.6	643213141.2

Source: World bank Database (accessed 27/06/24)