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MASTER OF MANAGEMENT IN FINANCE AND INVESTMENTS

A RESEARCH REPORT ON

Oil price shocks, oil and the stock market volatility relationship of Africa's emerging and frontier markets

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ABSTRACT

The study examined the relationship between oil price shocks, volatilities and stock indices in the African emerging markets. The ARDL and Bivariate BEKK GARCH models are used in this study. The countries examined are Botswana, Egypt, Mauritius, Morocco, Namibia, Nigeria, South Africa, Tanzania, Kenya, Ghana, Tunisia, and the MSCI's World Index. The study shows a bidirectional relationship between oil price shocks for Nigeria and the MSCI, but unidirectional flow from oil price shocks to Botswana, Egypt, Mauritius, Morocco, Namibia, South Africa, Tanzania, Kenya, Ghana, and Tunisia. In addition, there is evidence of unidirectional volatility spill over from oil returns to Botswana, Namibia, Tanzania, Mauritius and Kenyan, Nigeria, Tanzania, Kenya and Ghana. Finally, the study found bidirectional volatility between oil and index returns in MSCI, South Africa, and Tunisia.

DECLARATION

I, Makgalemele Molepo, Student Number: 740066, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in Finance and Investment at the University of the Witwatersrand, Johannesburg.
It has not been submitted before for any degree or examination in this or any other university.

Signature ---
Makgalemele Molepo

Signed at ……………………………………… On the ……………… day of ………………………… 2017

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CHAPTER 1

1. Introduction

The Financial Times Stock Exchange (FTSE) classify South Africa, Morocco, Egypt as emerging markets, while Ghana, Botswana, Kenya, Mauritius, Nigeria, Tunisia are classified as frontier markets (FTSE, 2016). Furthermore, FTSE (2016) defines frontier markets as small and relatively illiquid stock markets, but are increasingly becoming investable. According to Bekaert and Harvey (2002), a country is emerging if its per capita GDP falls below a hurdle that changes through time, but these countries can emerge from a less developed status and join the group of developed economies overtime. Emerging economies tend to import inflation as they import more goods than they export due to limited local manufacturing and are faced by relatively volatile exchange rates.

One of the major contributors to inflation in most emerging markets is the volatile oil prices. Oil is priced in hard currency (which may cause pressure on the real exchange rate) and enter the production process, thus affecting the cost of manufacturing of goods. The production of goods can become more expensive with higher oil prices in addition to local currency depreciation or have an effect on reducing production costs if prices go down. These oil price movements will eventually have an effect on the supply side of goods and services, and the aggregate demand side of the economy. Kaseeram, Nichola and Mainardi (2004) found that exchange rate depreciation increases inflation through labour union induced wage increases.

According to Jones and Kaul (1996), with all variables remaining constant, the exporters of oil are likely to benefit from an increase in oil prices, while the oil price increase is likely to affect importers of oil negatively. Eventually, the consumers will feel the rolling effect of these higher prices, which may lead to higher inflation and less consumer spending or lower inflation with cheaper oil price. Hooker (1996), Ferderer (1996) and Hamilton (1996) found a significant relationship between the movements of oil prices and macroeconomic variables.

On the production side, higher oil prices may incentivize producers of goods and services to reduce their supply or to increase product prices. The resulting higher prices of goods may influence equity prices through potentially higher profits. Alternatively, lower sales quantities may influence equity prices through lower revenues/profitability (Basher & Sadorsky, 2006). In addition, changes in consumer spending or other macroeconomic (i.e. inflation) variables induced by changes in oil prices may have an effect on the demand for companies' products and services which may reflect on their stock prices. In addition, Narayan and Narayan (2010) postulate that oil prices can affect the stock price through the discount rate consisting of both the expected inflation rate and expected real interest rates. This is because both inflation and exchange rate are a function of oil prices for a net importer of oil. In turn, the higher inflation will affect the discount rate, which in turn will influence the equity prices negatively. Huang, Masulis and Stoll (1996) indicate that oil can affect expected cash flows and discount rates because oil is a real resource and an essential input to production of goods. Changes in oil price will cause changes in expected costs and stock prices.

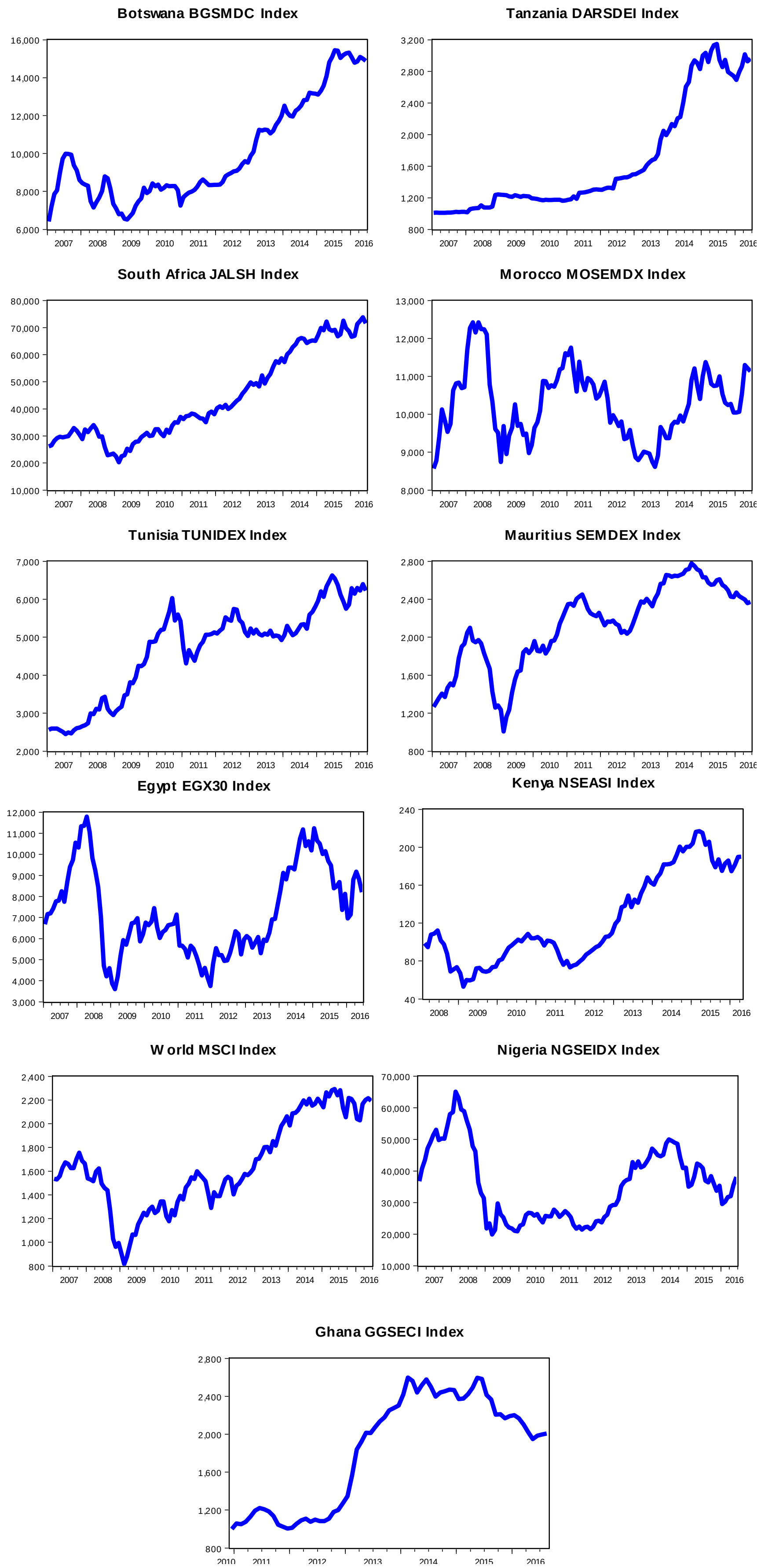

Figure 1 African stock markets trends

Figure 1 above depicts respective index pattern for the countries or markets investigated in this study. They include the following:

- Botswana Gaborone Index (BGSMDC);
- Tanzania all share index (DARSDEI);
- Egyptian EGX CASE 30 index(EGX30);
- South Africa’s JSE ALL SHARE INDEX (JALSH);
- Morocco’s MASI Free Float Index (MOSEMDX);
- Namibia’s FTSE JSE Namibia Overall Index (FTN098);
- Nigeria’s all share index (NGSEIDX);
- Kenya’s Nairobi Securities All Share Index (NSEASI);
- Mauritian all share index(SEMDEX);
- Tunisia’s all share index(TUNIDEX); and
- Ghana’s composite all share index (GGSECI) and MSCI World Index.

There is a fairly consistent upward pattern observed for JALSH, BGSMDC, DARSDEI and Morgan Stanley Capital International (MSCI). NGSEIDX, EGX30, MSCI and MOSEMDEX had a sharp downward trend in 2009, possibly due to the lagged effects of the 2008 economic and financial crisis. There is a recovery observed for MSCI and SEMDEX indices after 2009.

African and emerging equity markets are generally characterized by high volatility (See figure 1). This study empirically investigates the impact of oil price shocks on volatility movements on equity indices. It also reports on the magnitude of the relationship in the African emerging and frontier markets. The study further comparatively examines the impact of oil shocks prices on world markets, with MSCI index as a proxy. The African markets are chosen based on their market capitalisation, trade volumes and gross domestic product output. Data availability over longer periods is also an important factor in selecting these markets. The countries chosen for empirical investigation on the effect of oil price shocks on equity market are South Africa, Botswana, Namibia, Mauritius, Kenya, Tanzania, Nigeria, Egypt, Tunisia, Morocco, and Ghana. The regions are specified as North of Africa, West of Africa, East of Africa, and South of Africa.

The monthly data for all these countries (except for Kenya and Ghana) range for the period starting January 2007 ending the June 2016. Data for Kenya range from February 2008 to April 2016 and for Ghana, the data range from December 2010 to August 2016. The availability of sufficient long time series data for indices and consumer price index (CPI)[1] was a criterion for selecting these time frames. In addition, the range chosen covers a couple of financial turbulences that affected the oil price and financial markets. These include the 2008 financial crisis, 2011 European debt crisis, the Arab Spring and the movements of oil prices peaking at its highest in 2008 and falling to its lowest in 2015. The statistical descriptive for the countries is computed based on percentage returns as follows:

$$R_t = 100 * \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (1)$$

where R_t is the return at time *t*, P_t is the price of an index or stock at time *t*, and P_{t-1} is the previous price of an index, and *In* is the logarithm. Table 1 below shows the output of the descriptive statistics of South Africa's JSE index, Kenya's NSE index, Nigeria's all share index IDX and Egypt EGX 30 price return index.

Table 1 Descriptive statistics for monthly nominal percentage returns

	BGSMDC	BRENT	EGX30	SEMDEX	MOSEMDX	MSCI	FTN098	NGSEIDX	JALSH	DARSDEI	TUNINDEX	NSEASI	GGSECI
Mean	0.7451	-0.1278	0.1821	0.5551	0.2313	0.3149	0.4122	0.0291	0.8917	0.9535	0.7853	0.6688	1.0255
Median	0.8954	0.6340	0.5370	0.3798	0.0775	0.6404	0.6361	0.3570	1.2444	0.3388	1.0094	1.7227	0.8991
Maximum	11.5020	25.4459	24.93419	14.3211	10.3000	10.7138	16.0522	32.9962	11.7504	12.6260	9.1109	17.3064	15.7797
Minimum	-10.6975	-40.7402	-40.33121	-20.4513	-11.6503	-20.9880	-21.9189	-36.5761	-14.0709	-6.6483	-14.2611	-24.2709	-8.5869
Std. Dev.	3.6444	9.4289	9.6699	4.6053	3.8778	4.9686	6.1528	8.1029	4.4443	2.8469	3.9030	6.3668	4.2135
Skewness	-0.2021	-0.8013	-0.6677	-0.7162	0.0402	-0.9226	-0.5424	-0.5731	-0.3822	1.2638	-0.5160	-1.1547	0.8409
Kurtosis	5.1237	5.4829	4.9354	8.1701	3.4389	5.3062	4.7416	8.0237	4.0700	6.2818	4.8593	6.4424	5.6284
Jarque-Bera	22.0041	41.1195	26.0316	135.5158	0.9374	41.0708	19.8221	125.0136	8.1420	80.7929	21.2917	70.1642	27.5877
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0171	0.0000	0.0000	0.0000	0.0000
Obs	113	113	113	113	113	113	113	113	113	113	113	98	68

Table 1 above displays descriptive statistics for nominal monthly indices returns. All equity indices posted a positive average return, with GGSECI posting a highest average return of 1.0255%. Brent (crude) posted a negative return of -0.1278% over the period. EGX30 has the highest standard deviation of 9.6699%, followed closely by the Brent crude standard deviation of 9.4289. DARSDEI has the lowest standard deviation of 2.8469. The lower standard deviation seems to corroborate with the tranquillity of the DARSDEI index nominal returns plotted in Figure 8. All returns exhibit excess kurtosis and fatter distribution tails. The World Bank (2016) classifies South Africa as upper middle income, with GDP estimated at $312,798 billion in 2015 (World Bank, 2016). South Africa is situated in the southern region of Africa. South African equities are traded on the

[1] CPI index data is used for computing real returns

Johannesburg Stock Exchange (JSE). The JSE had a market capitalisation of $1,007 Billon (as of 31 December 2013) with 281 million shares traded daily (JSE, 2016). Figure 1 below depicts the all share index monthly nominal returns market movements of the JSE.

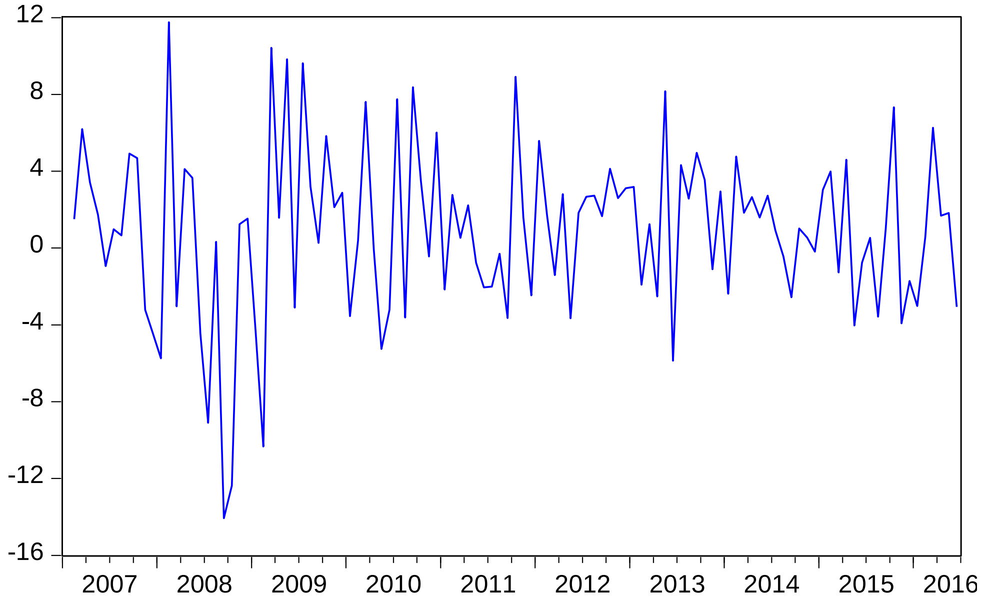

Figure 2 JSE All share index monthly returns

The standard deviation is 4.4443%. The maximum return for the period measured is 11.7504%, and the minimum return at -14.0709%. The mean is recorded at 0.8917%. Figure 2 shows what can be interpreted at this preliminary stage as evidence of volatility clustering in returns during 2008, 2011 and 2015/6[2].

Although classified as a lower middle income country by the World Bank (2016), Nigerian GDP output is estimated at $481,066 billion in 2015 (World Bank, 2016). Nigeria is situated in West Africa. The Nigerian Stock Exchange has a market capitalisation of $80.8 billion recorded in 2015 (Nigeria Stock Exchange, 2016). The number of shares traded daily is 152 million (NSE, 2016).

[2] These clusters were caused by the 2008 financial crisis originating from the United States. The 2011 crisis was caused by the European debt crisis which filtered into the South Africa markets. The 2015 volatility clusters was caused by the recalling of minister of finance, Mr Nhlanhla Nene by the President, Mr Jacob Zuma, which wiped out an estimated R500 billion of the markets as the Rand depreciated.

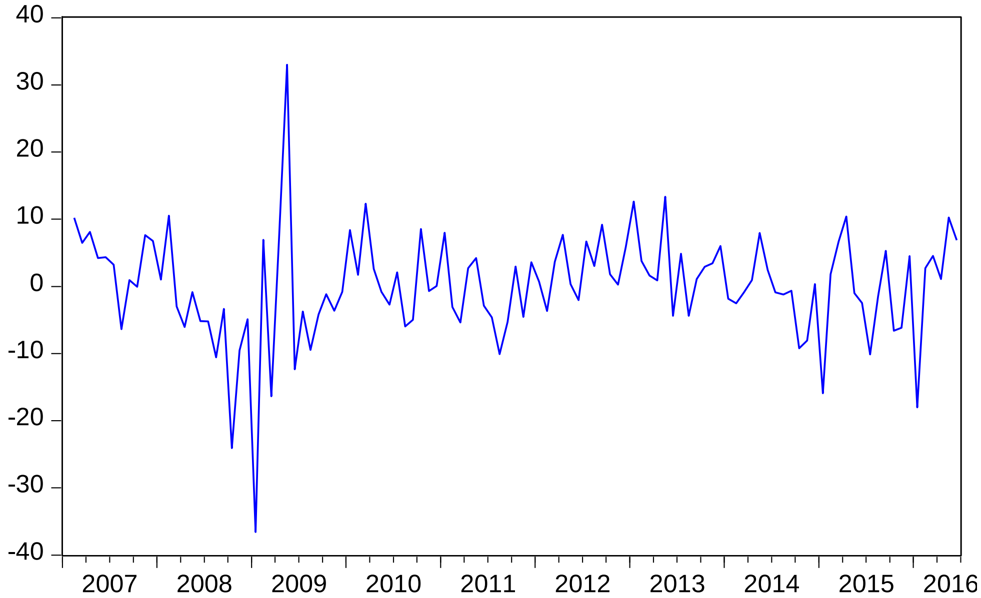

Figure 3 Nigerian all share index monthly returns

The standard deviation is 8.1029%. The maximum return for the period measured is 32.9962% and the minimum return at 36.5761%. The mean is recorded at 0.0291%.

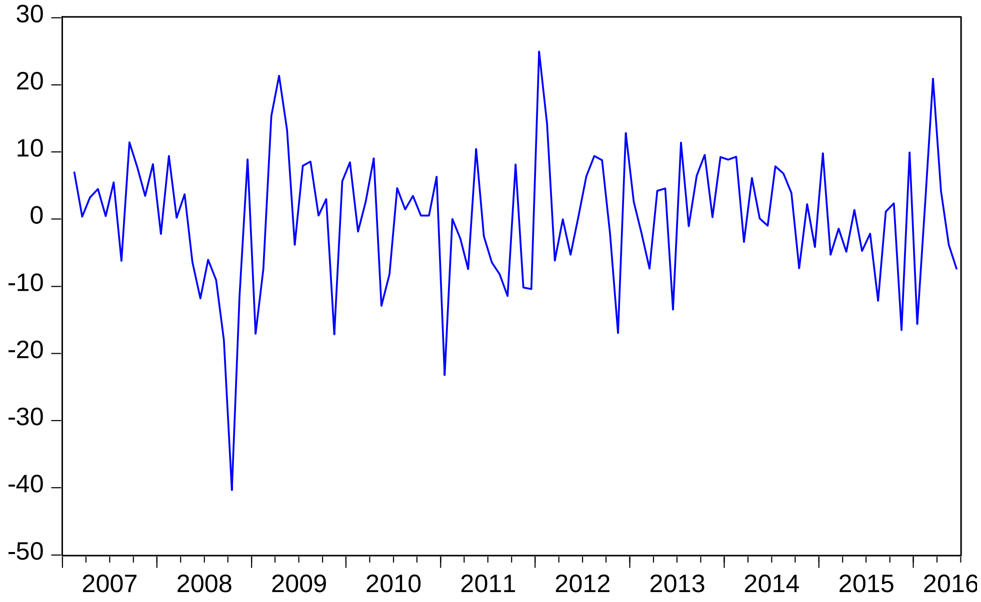

Figure 4 Egypt EGX 30 monthly price returns index

Egypt is situated in North Africa and is classified as lower middle income by the World Bank (2016). The GDP output is estimated to be $330,779 billion in 2015 (World Bank, 2016). The Egyptian stock market capitalisation was $55.1 Billion in 2015 (World Bank, 2016). The Egyptian Stock Exchange is trading 164 million shares daily (EGX, 2016). The standard deviation is 9.6699%. The maximum return for the period measured is 24.9342%, and the minimum return at -40.3312%. The mean is recorded at - 0.18212%.

Kenya is a lower middle income economy (World Bank, 2016) situated in East Africa. Kenya GDP is estimated to be $63.398 billion in 2015 (World Bank, 2016) compared to Tanzania, which has a GDP of $48.06 billion in 2015, and classified as low income by the World Bank (2016). Kenyan Nairobi stock exchange was founded in 1954, with over 60 listed companies and a market capitalisation of $23 Billion in 2015 (NSE, 2016). The standard deviation is 6.3668%. The maximum return for the period measured is 17.3064%, and the minimum return at -24.2709%. The mean is recorded at 0.6688%.

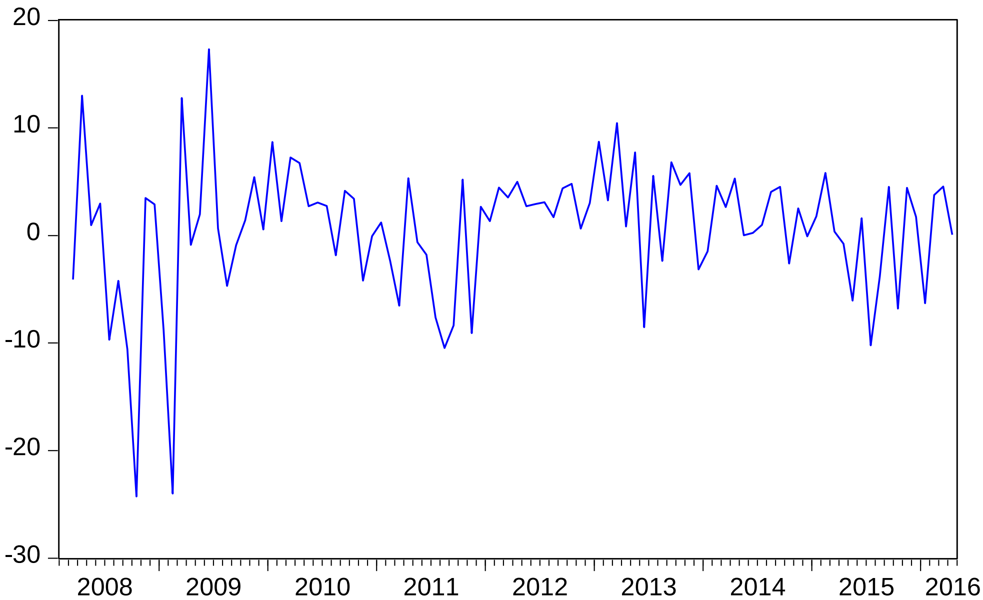

Figure 5 Nairobi all share index monthly returns

Botswana is the second biggest economy in the southern African region, and is classified by the World Bank as upper middle income, with a GDP of $14.391 billion in 2015 (World Bank, 2016). Botswana stock exchange was founded in 1989, with 33 listed companies and a market capitalisation of $56 billion in 2015 (BSE, 2016). The standard deviation is 3.6444%. The maximum return for the period measured is 11.5020%, and the minimum return at --10.6975%. The mean is recorded at 0.7451%.

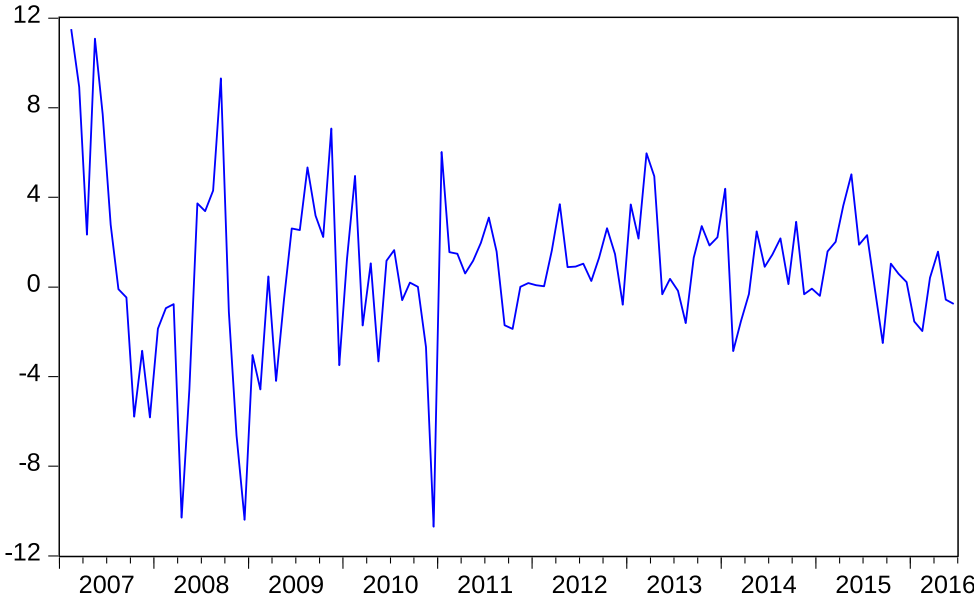

Figure 6 Botswana Index monthly returns

Mauritius is an upper middle income by the World Bank (2016), situated in Southern Africa. Mauritius GDP is estimated to be $11.551 billion in 2015 (World Bank, 2016). Mauritius stock exchange was founded in 1989, with 51 listed companies and a market capitalisation of $6.8 billion in 2015(SEM, 2016). The standard deviation is 4.6053%. The maximum return for the period measured is 14.3211%, and the minimum return at -20.4513%. The mean is recorded at 0.5551%.

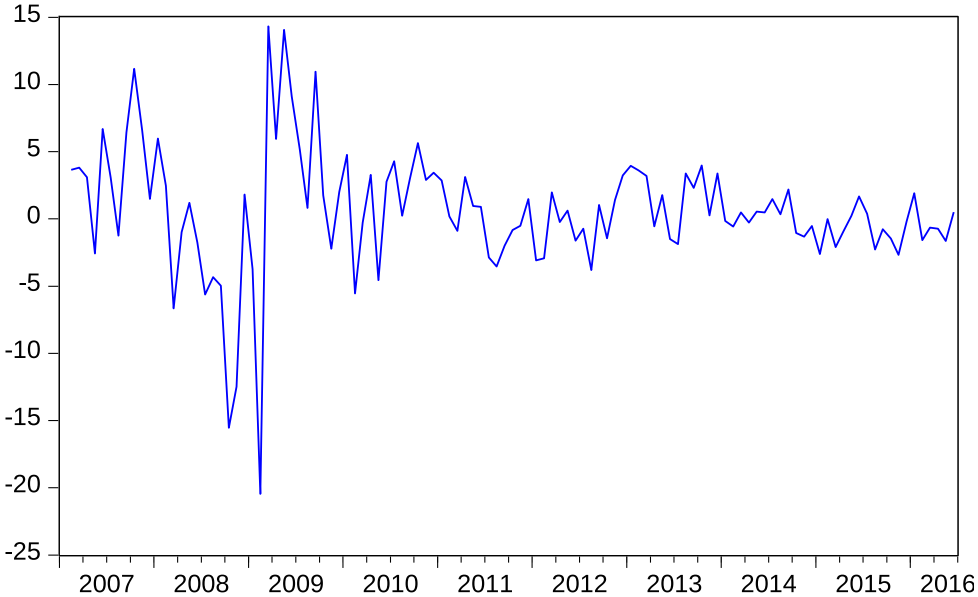

Figure 7 Mauritian stock index monthly returns

Namibia is an upper middle income by the World Bank (2016), situated in Southern Africa. Namibia GDP is estimated to be $11.546billion in 2015 (World Bank, 2016). The Namibian stock exchange was founded in 1904, with 38 listed securities, and a market capitalisation $139 billion in 2015 (NSX, 2016). The standard deviation is 6.1528%. The maximum return for the period measured is 16.0522%, and the minimum return at -21.9189%. The mean is recorded at 0.4122%. Namibia is closely linked to South African markets, with a sizeable South African firms listed in the Namibian stock exchange. These companies include Anglo American, Clover, Barloworld, Mediclinic, Afrox, Investec, and FirstRand (NSX, 2016).

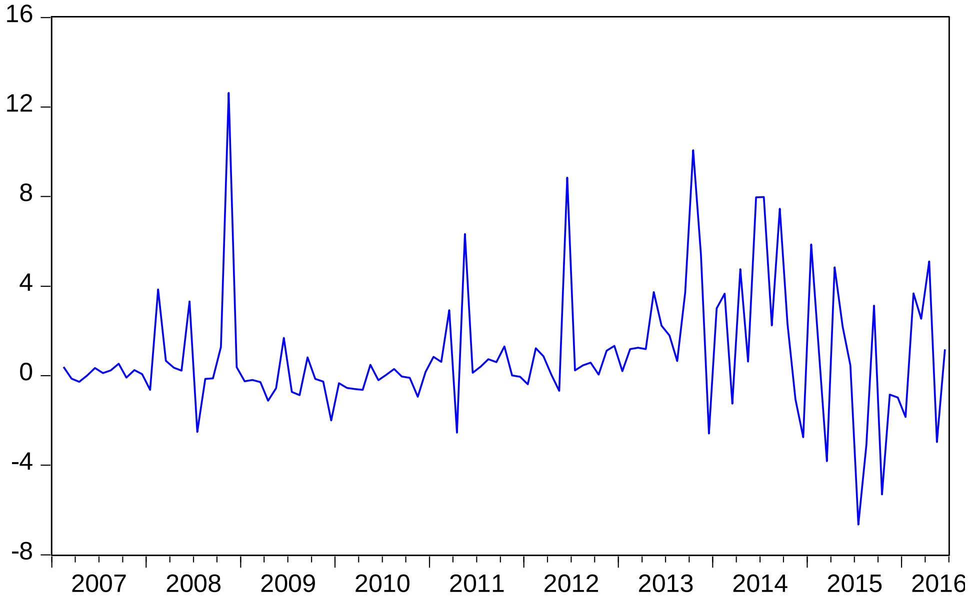

Figure 8 Tanzania index monthly nominal returns

According to the World Bank (2016), Tanzania is low income country situated in East Africa. Tanzania GDP is estimated to be $44.895 billion in 2015 (World Bank, 2016). Tanzanian stock exchange was founded in 1996, with 24 listed entities (DSE, 2016). Tanzania's Stock Exchange has a market capitalisation of $21 billion recorded in 2015 (DSE, 2016). According to the DSE (2016), the first commercial bank only listed on the exchange in 2008, followed by the first mining entity listing in 2011, hence the calmness and low volatility of the index. With low interest in the stock exchange, the stock exchange further launched the Enterprise Growth Market (EGM) in 2013 with the aim of facilitating or raising capital for small and medium enterprise, as these enterprises are considered key for wealth creation and employment creation. The launching of the enterprise growth market could have been the key factor in introducing volatile movements of the index in the Dar es Saalam Stock Exchange. The standard deviation is 2.8469%. The maximum return for the period measured is 12.6260%, and the minimum return at -6.6483%. The mean is recorded at 0.9535%.

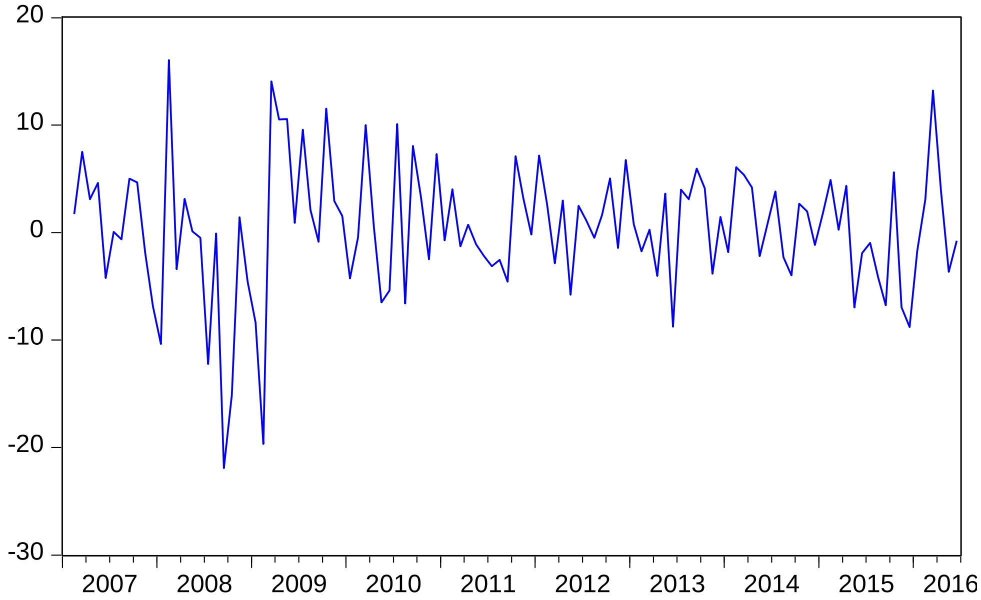

Figure 8 Namibia stock exchange

Morocco is a lower middle income according to the World Bank (2016), situated in Northern Africa. Morocco GDP is estimated to be $100.36 billion in 2015 (World Bank, 2016). Moroccan stock exchange was founded in 1929, with 75 listed entities (BVC, 2016). Casablanca Stock Exchange has a market capitalisation of $80 billion recorded in 2015 (BVC, 2016). The standard deviation is 4.6053%. The maximum return for the period measured is 10.3000%, and the minimum return at -11.6503%. The mean is recorded at 0.2313%.

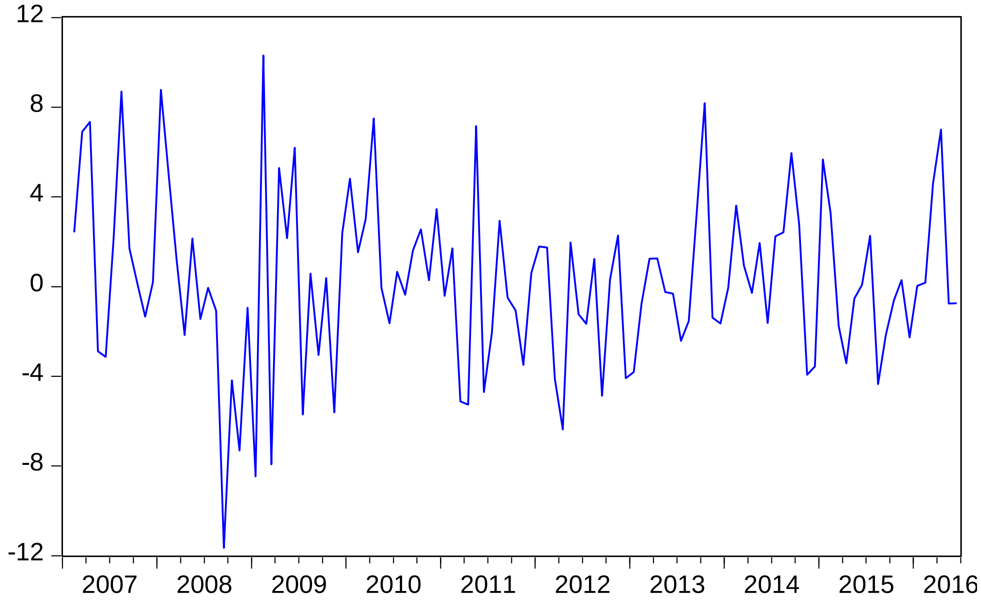

Figure 9 Morocco stock index nominal monthly returns

According to the World Bank (2016), Tunisia is an upper middle income economy situated in North Africa. Tunisia GDP is estimated to be $43.015 billion in 2015 (World Bank, 2016). Tunisia Stock Exchange was founded in 1969, with 80 listed entities (bvmt, 2016). Tunisia Stock Exchange has a market capitalisation of $80 billion for the year 2015 (bvmt, 2016)). The standard deviation is 3.9030%. The maximum return for the period measured is 9.1109%, and the minimum return at -14.2611%. The mean is recorded at 0.7853%.

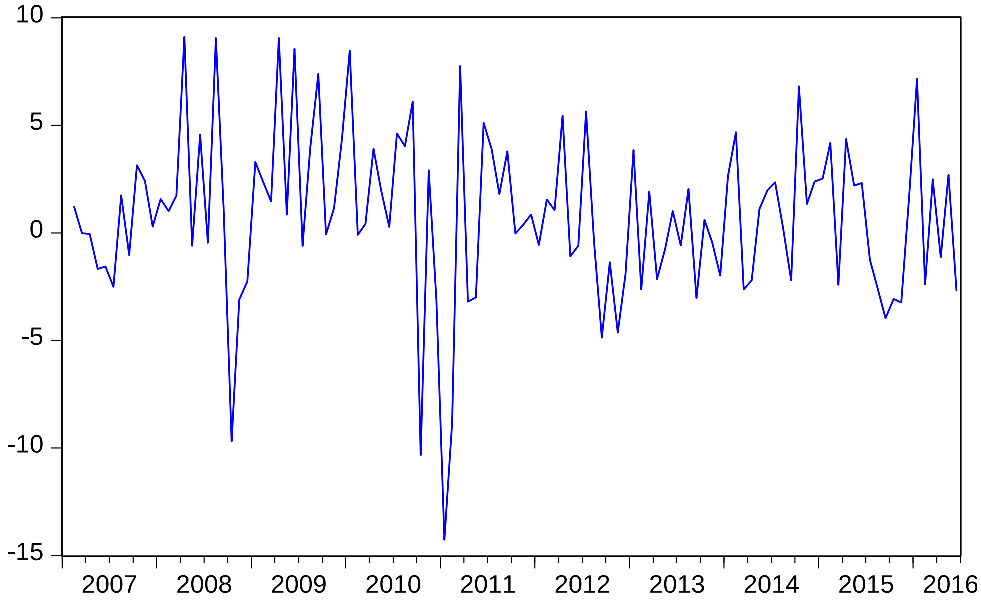

Figure 10 Tunisian stock index monthly returns

Ghana is a lower middle income according to the World Bank (2016), situated in Western Africa. Ghana GDP is estimated to be $37.864 billion in 2015 (World Bank, 2016). Ghana stock exchange was enacted in 1971, but was launched in 1991(gse, 2016). The standard deviation is 4.2135%. The maximum return for the period measured is 15.7797%, and the minimum return at -8.5869%. The mean is recorded at 1.0255%.

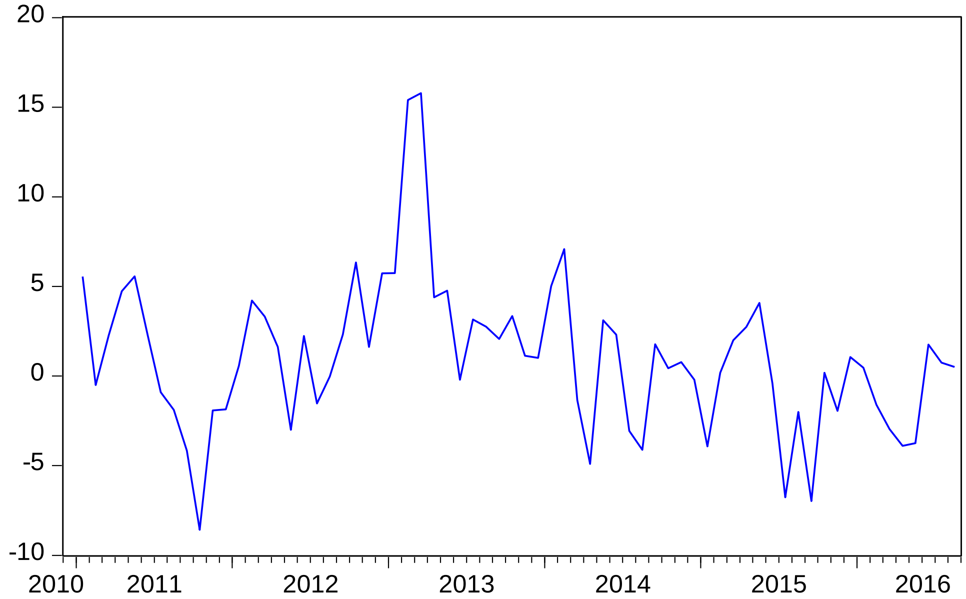

Figure 11 Ghana Index monthly returns

The MSCI world index was launched in 1986 as an independent provider of research for institutional investors (MSCI, 2016). The index is listed on the New York Stock exchange (NYSE) and includes equities from 23 markets around the globe. The index has 1645 equity constituents, and covers approximately 85% of the free float-adjusted market capitalization in each country (MSCI, 2016). The standard deviation is 4.9686%. The maximum return for the period measured is 10.7138%, and the minimum return at -20.9880%. The mean is recorded at 0.3149%.

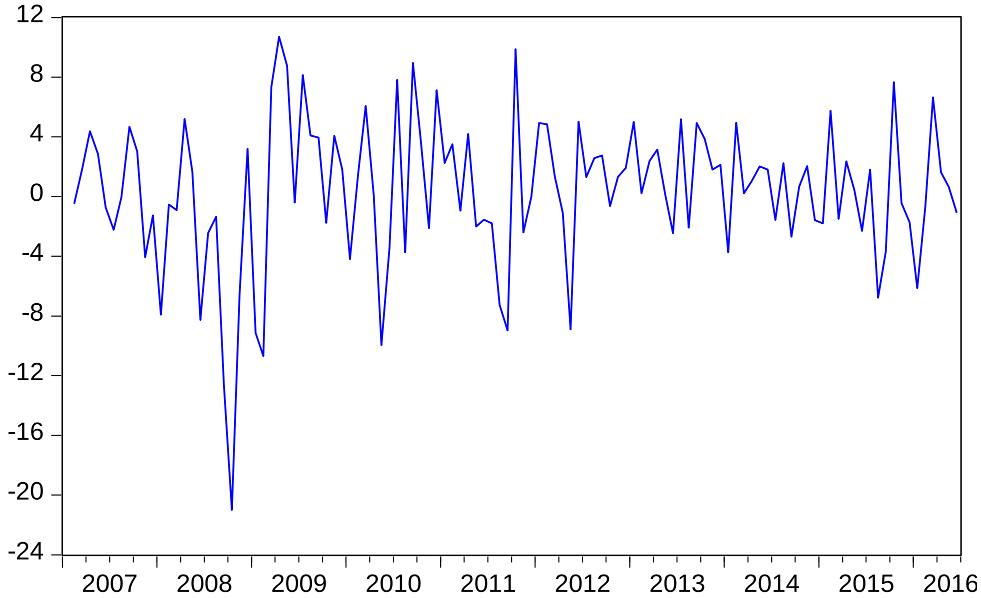

Figure 12 World MSCI index monthly nominal returns

2. Oil price pattern

Figure 5 below shows the trend of Brent crude oil prices from January 2007 to 2016. The price peaked at $146 in 2008, and its lowest prices at $27.88 in January 2016. The trend averages $ 86.6057per barrel.

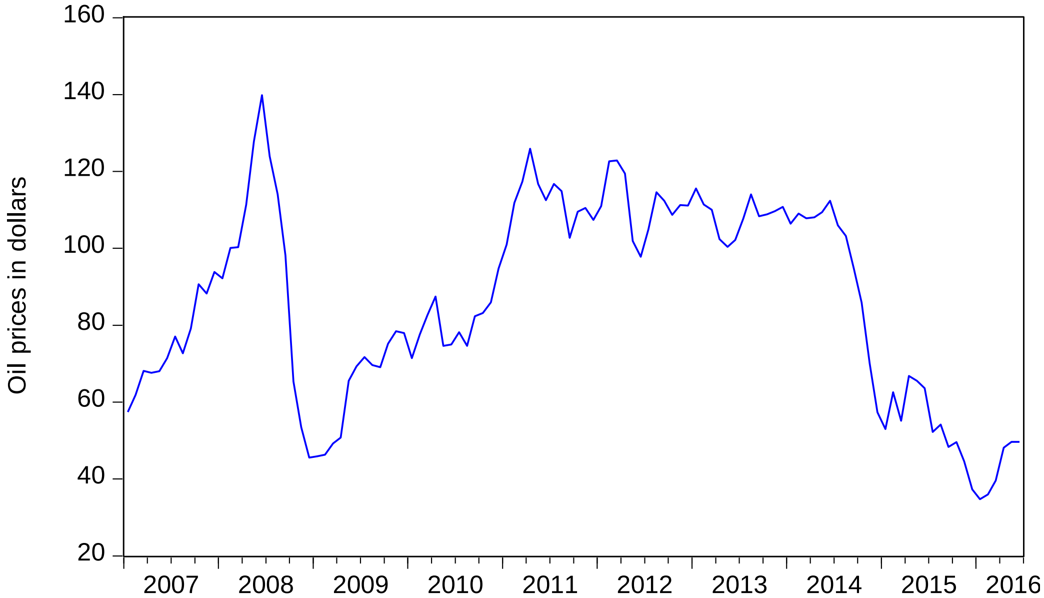

Figure 13 Brent crude price pattern

The Arab Spring revolution and the subsequent Libyan crisis of 2011 are some of the possible contributors to higher oil prices in the period between 2011 and 2014. The record rise in oil price in 2008 is attributed to the high demand from Asia, specifically from China and India[3], as the both countries were on a growth path. In addition, there were speculations of limited production of crude oil from exporting countries like Iraq, Iran and Nigeria. The limitation of production of oil was potentially attributed to political instability in Iraq, Iran's economic sanctions and instabilities in the Delta region in Nigeria. The oil prices plummeted again in 2008 as the world was in a recession. The prices dropped to around $40 a barrel by December of 2008. The oil price started rising again in 2009 due to demand from the Asian economies. There was relative stability from 2011 to 2014 as the world markets were stabilising from the 2008 financial crisis, even though the Libyan crisis was threatening the oil supply. The oil prices fell by 50% between June 2014 and January 2015, from $110 a barrel to $80 a barrel. The drop was mostly attributed to the weak demand from Europe and Asia and the decision by Organization of the Petroleum Exporting Countries (OPEC) not to cut oil production (Williams, 2016; Husain *et al.*, 2015).

[3] World Bank (2016) estimated China and India 2008 GDP growth to be 9.9% and 6.6% respectively.

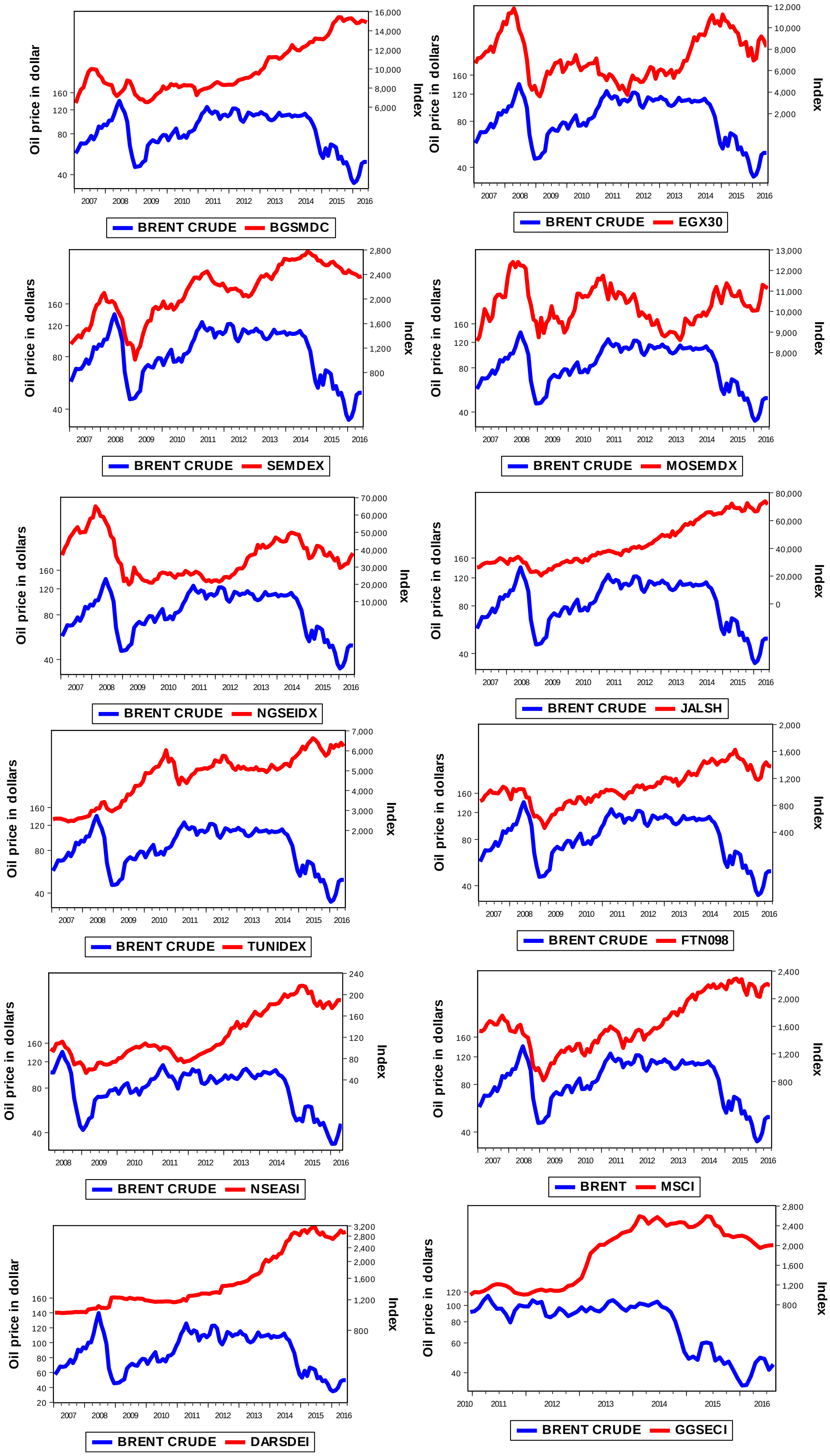

Figure 14 Brent crude and Index trend

As per Figure 14 above, there is a similar downward trend observed for Brent crude, EGX30, SEMDEX, MOSEMDEX, MSCI, FTN098, and NGSEGX between 2008 and 2009. A slight downward trend is also observed for TUNIDEX and JALSH during the same period. Brent crude continued with the downward trend after relative stability between 2010 and 2014. Most of the indices showed a recovery, showing an upward trend after 2014.

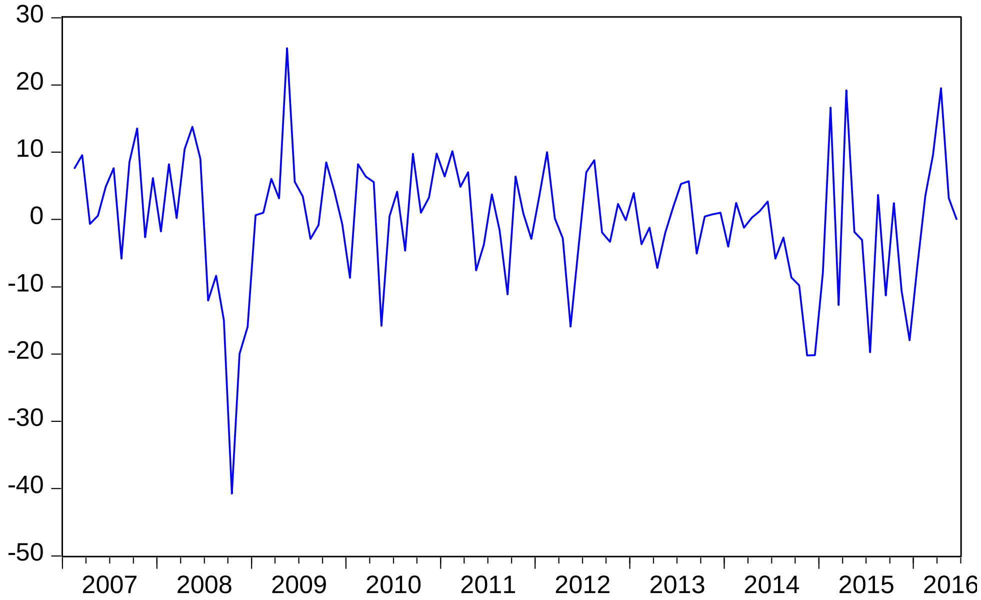

Figure 15 Brent crude monthly price returns

The standard deviation is 9.4289%. The maximum return for the period measured is 25.4459%, and the minimum return at -40.7402%. The mean is recorded at -0.1278%. Oil prices are linked to world markets. There is evidence of volatility clustering between 2008 and 2009, in 2010, between 2011 and 2012 and lastly, between 2015 and 2016.[4] These clusters are similar to South African index and MSCI index returns. According to the Global Competitive Report (2015), South Africa has higher quality financial institutions, with a higher financial market development in Africa. Furthermore, there is a high accountability of private institutions. In addition, the report adds that South Africa has very strong ties with advanced economies, especially the European area, which makes it more exposed to economic slowdowns of those economies.

[4] Various reasons could have contributed to the observed volatility clustering. For example, the 2008 financial crisis, the 2011 Arab spring and European debt crisis, and the slower than anticipated economic growth in China in 2015 (World Bank, 2016), which would have resulted in reduced demand for oil.

3. Objectives of the study

The objectives of this study are to:

- Examine the behaviour of stock markets across time within the chosen African markets.
- Explore the relationship between stock market volatility and oil price variations in the sampled countries.

4. Purpose of the study

This study will contribute to the literature on oil prices and equity prices by studying the effect of oil price fluctuations on African emerging and frontier stock markets. There are a number of studies investigating relationship between oil prices and equity markets, but most of these empirical investigations are from developed markets (United States of America, Japan, Norway, and United Kingdom). Those that are empirically investigated from an emerging market perspective are mainly focused on Asian, Middle East or Latin American markets (for example, China, Vietnam, Saudi Arabia, Kuwait, Qatar, Jordan, Venezuela, Brazil, and Argentina). This paper will further contribute to institutional and individual investors who have interests in investing in the African emerging and frontier equity markets.

5. Problem statement

Oil price movements have been volatile over the years. According to the International Monetary Fund (IMF) report of 2016, oil prices declined by 55% from November 1996 to December 1998, and by 67% from July 2008 and December 2008. This coincided with an average GDP decline in the sub-Saharan countries from 5% in 1996–1997 to less than 3% in 1998–1999 and a decline of 2 percentage points in 2009–2010 respectively. The GDP growth was down as oil exporters started to adjust to lower global oil prices, while in South Africa, mining strikes and electricity constraints had an additional effect (IMF, 2016). The Ebola outbreak had a significant effect on some of these countries. As an oil exporter, Nigeria has been hit hard by the oil price decline and having an effect on the country's GDP (IMF, 2016). Furthermore, the IMF report states a 43% oil price decline in 2014, resulting in slightly higher economic projections of 5% in 2015 to 2016 compared to higher actual real GDP growth of 4.5% in 2013–2014. There is evidence that variation of oil prices does have an effect on the stock markets. For instance, Narayan and Narayan (2010) found that oil prices have a positive and statistically significant impact on stock prices. This study empirically investigates the effect of oil price shocks on equity in African emerging and frontier markets. In addition, the problem investigated is if the nature of the relationship depends on whether the country is a producer or a non-producer of oil.

CHAPTER 2

2.1 Literature review

2.1.1 Explaining volatility in stock markets

Various factors characterise volatility in the financial markets. The quick rise and fall of markets can be caused by macroeconomic variables, movement of commodity prices, politics, financial instabilities, and spillovers from other markets (Gomes & Chaibi, 2014). Koutmos and Booth (1995) found evidence of the volatility spillover between the New York, Tokyo and London stock exchanges. Bomfim (2003) indicates that the interest rate decisions tend to boost market volatility in the short-term. In addition, Chinzara (2011) found evidence of macroeconomic uncertainty significantly influencing stock market volatility in South Africa. Mattes (2012) found evidence of the credit crises of 2008 significantly contributing to volatility in the Nigerian, South African, Kenyan, Mauritian, and Egyptian markets. Alagidede and Panagiotidis (2009) found evidence of volatility clustering, leptokurtosis, and leverage effects being present in the African stock index returns of South African, Kenya, Zimbabwe, Nigeria, Tunisia, and Morocco. Aggarwal, Inclan and Leal (1999) examined volatility in emerging Latin American markets and examined the global events, like social, political and economics. They found that most events contributing to the volatility tends to be local, like the Mexican peso crisis, hyperinflation in Latin America, the Philippines conflict, and the Indian stock market scandal. They found the only global occurrence affecting volatility was the 1987 financial crash. The emerging markets investigated are all in Asian and Latin American regions.

2.1.2 Oil price shocks and volatility in equity prices

Basher and Sadorsky (2006) investigated the impact of oil price changes in emerging markets. The emerging markets investigated are Brazil, China, India, Indonesia, Japan, Malaysia, Pakistan, Russia, and Thailand. They used a form of the international capital asset pricing model (ICAPM), which allows for both conditional and unconditional risk factors with data from the Morgan Stanley Capital International (MSCI) world index, ranging from 31 December 1992 to 31 October 2005. Their investigations found strong evidence that oil price shocks do have an impact on stock markets of emerging countries. The correlation of oil price and equity returns was found to be statistically significant at the 10% level.

Cong, Wei, Jiao, and Fan (2008) focused on the relationship between oil price shocks on the Chinese stock markets. They used the stock market indices, manufacturing index and stocks from other oil companies. They used the multivariate vector auto-regression (VAR) model to investigate their empirical study. They used data collected from the Shanghai and Shenzhen stock exchanges for equity markets, industrial data from the National Bureau of Statistics of China and oil price data from United States Energy Information Administration (EIA). They used data ranging from January 1996 to December 2007. Their investigation found that oil prices have an impact on stock returns of one industry index, and two oil companies. The nature of relationship of stock returns and oil price shocks is statistically significant at the 5% level.

Narayan and Narayan (2010) estimated the impact of oil process on Vietnamese stock prices using the VAR model. They used the oil price from the West Texas Intermediate (WTI) index and the equity price from the Vietnam Stock Exchange. The data were extracted from the Bloomberg terminal, and it ranged from 28 July 2000 to the June 2008. Their empirical research found a positive and statistically significant relationship between oil prices and equity prices at the 1% level: a 1% increase in the oil price has an impact of 1.3% increase in the Vietnamese equity market.

Dagher and Hariri (2013) investigated the impact of global oil price shocks on the Lebanese stock market. They used the VAR framework, using daily closing prices for the period 10/16/2006 to 7/10/2012 obtained from the EIA. They found evidence of oil price shocks Granger causing the stock markets, but no evidence of stock market Granger causing oil price shocks. Bouri (2015a) investigated the return and volatility linkages between oil prices and the Lebanese stock market in the crisis periods using the Vector Autoregressive-Generalized Autoregressive Conditional Heteroscedasticity (VAR-GARCH). Bouri (2015a) used weekly data from 30 January 1998 to 30 May 2014 and found interrelations between oil and stock volatility increasing during the crises periods, but generally found volatility spillovers to be from oil price return to the Lebanese stock market index return.

Degiannakis, Filis and Kizys (2014) investigated the effects of oil prices on stock market volatility from European data. They differentiated the oil shocks into three variables, namely the supply-side, aggregate demand and oil specific demand shock. They used the structural VAR framework. They used the Eurostoxx index data, which they extracted from DataStream. They used Brent crude oil price as a proxy for world oil price, oil production data as a proxy for the supply side, and measured global economic activity based on dry cargo freight rate. Their findings are that supply side and oil specific demand shocks do not affect stock volatility, but aggregate demand shocks do influence volatility.

Gomes and Chaibi (2014) empirically examined the shocks and volatility between oil prices and equity prices in the frontier markets. The markets research were from Argentina, Bahrain, Bulgaria, Jordan, Kazakhstan, Kenya, Kuwait, Lebanon, Mauritius, Nigeria, Oman, Pakistan, Qatar, Romania, Saudi Arabia, Slovenia, Sri Lanka, Tunisia, United Arab Emirates, Ukraine, and Vietnam. Their investigations show that oil price shocks effect a change in stock markets return in Jordan, Kenya, Lebanon, Oman, Qatar, Saudi Arabia, UAE, and Ukraine at a 1% significant level, while the effect is at 5% in the Nigerian market and 10% significant level in the Vietnam market.

Chittedi (2012) investigated the long-run relationship between oil price and stock prices for India. Data used covered the period of April 2000 to June 2011. The results suggest that a change in oil prices does not affect stock prices, but suggests that volatile stock prices have an impact on the volatility of oil prices. Using the multivariate VAR–GARCH model, Lin, Wesseh Jr and Appiah (2014) found empirical evidence of significant volatility and shock spillover from oil to Ghanaians and Nigerian indices. They used weekly data ranging from 7 January 2000 to 31 December 2010. The level of significance was at 1% for both Ghana and Nigerian markets.

Studying the United States and 13 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Spain, Sweden, and U.K.), empirical evidence shows a statistically significant relationship between oil price shocks and on real stock returns (Park & Ratti, 2008). The study was conducted with a multivariate VAR using data from January 1986 to December 2005. They found a negative but statistically significant relationship between oil price shock and real stock returns in the US and 10 European countries, excluding Norway, Finland and United Kingdom. In addition, it was found that the relationship varies between negative and positive in some months of some other countries. For Norway, there is a positive, statistically significant relationship at 5% level in the same month between the oil price shock and real stock returns, but statistically insignificant for a lag on a month. Finland shows the negative relationship at 10% level of significance with returns lagged for one month. Donoso (2009) found that the oil prices changes affect the stock market variance by 9.51% in the US, 7.51% in the UK and 4.4% in the Japan.

According to Teulon and Guesmi (2014), there is a time varying correlation between the oil and stock markets in emerging and oil producing markets. Furthermore, the relationship between oil prices and stock market returns is found to be influenced by the origin of shock to oil prices. In addition, the stock markets responded stronger to political turmoil (demand side shocks) than to cuts in oil production (supply side shocks). They also found evidence of volatility spillovers between oil and stock markets. The empirical investigation was done in Venezuela, the United Arab Emirates, Saudi Arabia, and Kuwait. They used the multivariate GARCH to test conditional correlations between oil and stock prices.

Arouri and Rault (2012) conducted an empirical investigation on the relationship between oil prices and stock markets in various countries in the Gulf Cooperation Council (GCC). The countries in the GCC are Bahrain, Oman, Kuwait, Qatar, United Arab Emirates, and Saudi Arabia. All these countries are oil-producing countries. They found evidence of co-integration between oil prices and stock markets. In addition, they have found that an oil price increase has a positive impact on stock price in all investigated countries, except for Saudi Arabia. The data used are for the period from January 1996 to December 2007. Another study investigated the effect of change in oil price volatility in the stock market of the group of seven (G7) Germany, France, UK, Japan, Italy, and Canada economies. Diaz, Molero and Gracia (2016) used monthly data for the period 1970 to 2014. They used the VAR model with variables like interest rate, stock returns, oil price volatility, and economic activity. Their empirical findings are a negative response of G7 stock markets to an increase in oil price volatility. In addition, their findings indicate that the world oil price volatility is generally more significant for stock markets than the national oil price volatility.

Applying the Structural Vector Auto-regression (SVAR) model, Li, Cheng and Yang (2017) investigated the impact of oil shocks in the form of oil supply shocks, global demand shocks, domestic demand shocks and precautionary demand shocks. They used data from the Chinese listed companies in the oil industrial chain, ranging from 2009 to 2014. They found that the impact of oil supply shocks and precautionary shocks are the most significant. In addition, their finding suggest a gradual increase in the aggregate contribution price shocks to the changes in stock returns, and that oil industrial chain benefit from the oil price increase. Cunado and Gracia (2014) conducted an empirical investigation on the impact of oil price shocks in 12 oil importing European countries (Austria, Belgium, Denmark, Finland, France, Germany, Italy, Luxembourg, Netherlands, Spain, Portugal, and the United Kingdom (UK)) using the monthly data ranging from February 1973 to December 2011. They used the VAR and vector error correction model (VECM) to model the data. Their findings suggest that the response of the European stock market to the oil price shocks is dependent on the underlying cause of the oil price change and the stock market returns are mostly driven by the oil supply shocks.

Using the aggregate and sector level, Singhal and Ghosh (2016) conducted an empirical investigation of time varying co-movements between crude oil and the Indian stock market returns resulted in direct volatility spillover from the oil market to the Indian stock market not being significant at aggregate level, significant in the sector level of auto, power, and the finance. They used weekly data ranging from January 2006 to February 2015. They applied the VAR-DCC-GARCH model for their empirical investigation.

Aloui, Nguyen and Njeh (2012) used daily sample data of 25 emerging market countries (Egypt, Morocco, South Africa, China, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Taiwan, Thailand, Jordan, Turkey, Czech Republic, Hungary, Poland, Russia, Argentina, Brazil, Colombia, Chile, Mexico, Peru, and Venezuela) ranging from September 1997 to November 2007. They found that oil price risk is conditionally more relevant for emerging market stocks pricing. Furthermore, they also found asymmetry of oil sensitivity of stock returns being significant when the oil price rise, especially with markets that are positively correlated with the oil price movements. They used the rolling correlation technique with conditional multifactor asset pricing model. Mohanty, Nandha, Turkistani and Alaitani (2011) investigated the link between oil price changes and stock prices in the Gulf Cooperation Council (GCC) countries. They used weekly data ranging from June 2005 to December 2009 and used the linear factor-pricing model. They found that on the aggregate level, stock prices have significant positive exposure to oil price shocks, while from an industry level, 12 out 20 countries show significant positive to oil price shocks. An empirical study by Jouini (2013) found evidence of return and volatility transmission between oil price and stock sectors in the Saudi Arabian market, but the spillover effects are unidirectional from oil to some sectors for returns. Using the VAR-GARCH model, Jouini (2013) used weekly data ranging from January 2007 to September 2011.

Mohanty, Nandha and Bota (2010) found no significant relation between equity values of oil and gas firms and oil price movements. Their empirical study was done in five Eastern European countries in the Czech Republic, Hungary, Poland, Slovenia, and Romania. They used the monthly sample period ranging from December 1998 to March 2010, using the linear factor pricing model technique.

Assessing the impact of oil returns on emerging stock markets, Asteriou and Bashmakova (2013) used the multi-factor model, which allows for conditional and unconditional risk factors. They used daily closing prices data from October 1999 until 23 August 2007. The countries included in the study are Czech Republic, Lithuania, Estonia, Slovenia, Hungary, Latvia, Romania, Russia, Poland, and Slovakia. They found that the market beta is statistically significant and positive for all countries. This indicates positive trade-offs between market risks and stock market return, while the oil return coefficient is statistically significant and negative, suggesting that the oil price does affect stock returns. An increase in oil price returns causes the decrease in stock market return.

Ahmadi, Manera and Sadeghzadeh's (2016) study provided relationship between oil market and US stock market returns at the aggregate and industry level. They found that the stock returns respond to oil price shocks differently, which is dependent on the cause of the shocks. They also found that the consumption demand shocks are the most relevant drivers of the stock market return compared to other shocks of speculative demand and supply shocks. They applied the SVAR model using monthly data ranging from March 1973 to December 2013 extracted from the EIA.

Tsai (2015) investigated how US stock returns respond differently to oil price shocks prior to, during and after the financial crisis. The evidence suggests that US stocks respond positively to the changes in oil prices during and after financial crisis. The study also suggests that energy intensive manufacturing industries respond more positively to oil price shocks compared to less energy intensive manufacturing industries. In addition, the study found that big firms are the most strongly and negatively influenced by an oil price shock prior to a crisis and that the oil price shock in the post-financial crisis period is positively amplified in the case of medium-sized companies. Tsai (2015) used the ordinary least square (OLS) model with panel-corrected standard errors. They used daily data from 1990 to 2012.

Malik and Ewing (2009) conducted an empirical investigation on the mean and conditional variance between five different US sector indexes and oil prices. The sectors examined are financial, technology, consumer services, health care, and industrial sectors. They used weekly returns from 11 January 1992 to 30 April 2008. They found evidence of significant transmission of shocks and volatility between oil prices and some of the investigated factors. They used the bivariate GARCH model. Arouri, Jouini and Nguyen (2011) found significant volatility spillovers between oil and sector returns in Europe and USA. The stock return sectors are the automobile and parts, financials, Industrials, basic materials, technology, telecommunication and utilities. The used the VAR-GARCH model, using weekly data ranging from 1 January 1998 to 31 December 31 2009.

2.1.3 Summary of findings in the extant literature

Empirical investigations in the literature confirm that volatility in financial markets may be attributed to several macroeconomic variables and spillovers from other markets. From an African market point of view, oil price shocks have not been empirically investigated as the potential cause or contributor to volatility in some of the markets investigated (i.e. Namibia, Botswana, Tanzania, and Egypt), with South Africa, Kenya, Mauritius, Tunisia, and Nigeria being previously empirically examined, though with different time frames.

Furthermore, relationships of the above findings did not measure the effect variable of oil price in the African equity markets. Most of these results showing empirical relationship between oil price shock and stock market volatility were from developed countries, including the US and Europe (Park & Ratti, 2008; Degiannakis et al., 2014; Donoso, 2009; Tsai, 2015; Ahmadi et al,2016; Cunado & Gracia, 2014; Diaz et al., 2016). Some empirical investigations were done on the Asian and Latin markets (Singhal & Ghosh, 2016; Li et al., 2017) and other emerging markets from the Middle East and Eastern Europe (Mohanty et al., 2010; Mohanty et al., 2011; Jouini, 2013; Asteriou & Bashmakova, 2013). However, only two studies (Gomes & Chaibi, 2014; Aloui et al., 2012) in the literature appears to have used some African data: The recent studies of Aloui et al., (2012) and Gomes and Chaibi (2014) included Egypt, Morocco, South Africa and Kenya, Mauritius, Tunisia, and Nigeria in their empirical investigation using GARCH and multifactor asset pricing models between oil price shocks and equity market indices respectively. However, their studies focused only on volatility spillovers between stock returns, oil price changes, long-term correlations and oil pricing. This study goes beyond their study both in terms of the number of countries covered in Africa and in terms of focus, as shown in the study's objectives. This empirical investigation will use, among others, the auto regressive distributed lag (ARDL) to test long and short relationship in addition to the direction of the causality between the variables and the bivariate GARCH.

CHAPTER 3

3.1 Methodology

3.1.1 Oil shocks

All data for stock and CPI indices were extracted from Bloomberg.

Oil price shocks are defined with linear and non-linear specifications. Linear oil price shocks are defined as the percentage change in the price of oil, positive oil price changes, the difference between the current oil price and the previous year's maximum if positive, and the non-linear measures of oil prices shocks are the volatility within the price movements (Park & Ratti, 2008, Mork, 1989; Hamilton, 1996; Chen, 2010).

The CIOP is presented as follows (Chen, 2010; Adeniyi, Oyinlola & Omisakin, 2011):

$$o_t = \Delta \log(op_t) = \log(op_t) - \log(op_{t-1}); \qquad (2)$$

Where op is the Brent crude oil price and o_t is the CIOP.

Hamilton (1996) defined net oil price increase (NOPI) by the value of the current oil price if it exceeds the maximum oil price over the previous periods. Otherwise, it takes the value of zero. NOPI value of the current oil price is as follows (Chen, 2010):

$$NOPI_t = \max(0, \log op_t - \max(\log op_{t-1} \ldots\ldots \log op_{t-12}) \qquad (3)$$

Mork (1989) suggests a capture of only the positive oil price changes. The model is presented as follows (Chen, 2010):

$$o_t = \begin{cases} \Delta \log(op_t) & \text{If } \Delta \log(op_t) > 0 \\ 0 & \text{Otherwise} \end{cases} \qquad (4)$$

Where op is the oil price and o_t is OPI.

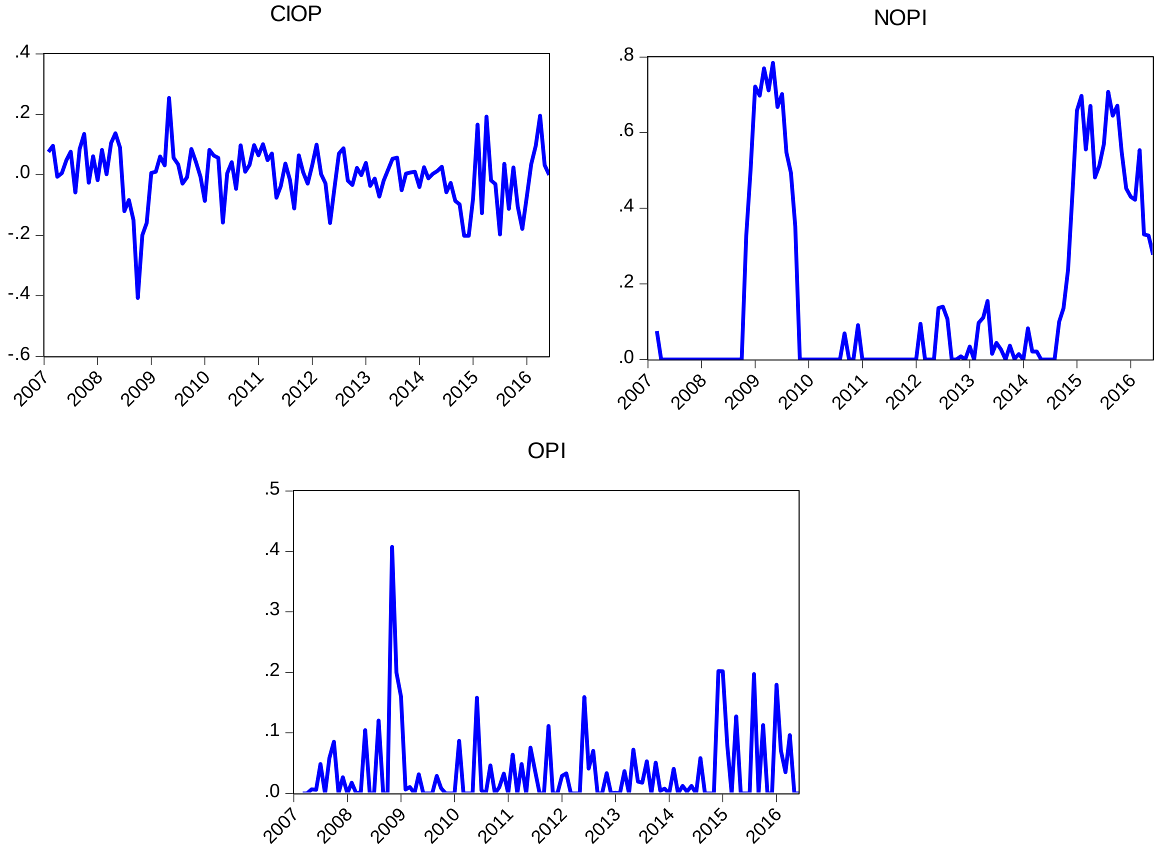

Figure 16 Oil price shocks (CIOP, NOPI and OPI)

Figure 16 above displays the different measure of oil price shocks as presented by equations 2, 3 and 4 above.

The NOPI variable is the oil price shock variable empirically investigated in this study. This variable is chosen because Hamilton (1996) argues that a measure of oil increase has an effect on the spending decisions of both households and firms with current oil price to its historical path, rather than the previous month alone. The effect of firms and household spending might have an effect on the firms' costs and profits, which in turn will affect stocks price in the long-run. In addition, Adeniyi et al. (2011) indicate that with the NOIP variable, it is possible to examine the causal relationship between important oil price increases and other variables, including the macroeconomic indicators.

Volatility of both stocks and Brent crude oil are estimated using the GARCH (1, 1).

$$R_t = \mu_i + \sum_{i=1}^{k} a_i R_{t-1} + \varepsilon_t \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0,h) \tag{5}$$

$$h_t = b_0 + b_1 \varepsilon_{t-1}^2 + b_2 h_{t-1} \tag{6}$$

Where R_t is the conditional mean equations of stock index and Brent crude oil[5] real returns, ε_t is the error terms of the conditional mean equation of stock and Brent crude oil returns, h_t is the conditional variances of real stock index return and real Brent crude oil returns, $b_1\varepsilon_{t-1}^2$ is the ARCH effects of information based on the previous periods, $b_2 h_{t-1}$ is the GARCH effects based on the fitted variance from the model during the previous period.

The Augmented Dickey Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are performed on all the series to test for stationary to avoid spurious estimations results. In addition, the bound and Granger non-causality tests were conducted to examine the long-and short-term relationships by estimating an ARDL between the oil price shocks and equity returns, and the Bivariate GARCH to examine the oil price shocks and volatility in the equity markets.

3.1.2 Augmented Dicky Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationery tests

The stationary tests were carried out using both the ADF and KPSS tests. The main reason was that the ADF unit root testing power tends to be low if the process is stationary with a root close to the non-stationary boundary (Brooks, 2014). To circumvent this problem on the ADF, a KPSS stationary is carried out jointly with the ADF unit root testing.

For ADF, consider the AR (1) model as follows (Mushtaq, 2011):

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \varepsilon. \tag{7}$$

The *t* statistics for the null hypothesis is given by:

[5] Brent crude oil return is adjusted using the United States CPI index. Stock Index returns are computed by the CPI level index of a country aligned to the index (log (CPI Index)). The results of the monthly difference of the log of CPI index (**log (CPI)-log (CPI (-1) = dlog (CPI))** is subtracted from the nominal returns of the stock index to give real returns **(dlog (index)-dlog (CPI (-1)).** CPI level indices are also seasonally adjusted.

$$t = \frac{\gamma^{\wedge} - \gamma H_0}{SE(\gamma^{\wedge})} \quad (8)$$

If the *t* calculated is greater than the critical values in absolute value terms or more negative than the critical value, then the null hypothesis is not rejected, which will indicate that the series will be non-stationary and will have a unit root. If it is less than the critical value, then the null will be rejected, indicating no unit root or stationary.

For KPSS, the *t* statistics is as follows (Ajayi & Mougoue, 1996):

$$t = T^{-2} \sum \left(\frac{S_t^2}{S^2(L)} \right) \quad (9)$$

where

$$S^2 = T^{-1} \sum_{t=1}^{T} e_t^2 + 2T^{-1} \sum_{s=1}^{L} \left(1 - \frac{S}{L+1} \right) \sum_{t=s+1}^{T} e_t e_{t-s} \quad (10)$$

and,

$$S_t = \sum_{i=1}^{t} e_i, t = 1,2,3,......,T. \quad (11)$$

T is the number of observations, e_t are the residuals obtained by regressing the series being tested on a constant, and *L* is the lag length. If the *t*-test statistic is less than the critical values, the null hypothesis of a stationarity series is accepted, indicating that the series is stationary. If the *t*-test statistic is greater than the critical values, the null hypothesis of stationary series is rejected, indicating that the series is not stationary.

3.1.3 Auto regressive distributed lag (ARDL)

The paper examines the relationship between oil price shocks and equity markets using the ARDL *F* bound testing. The ARDL is chosen to test the relationships as it has advantages and it can be applied regardless of the samples size. The sample size can be either small or larger. In addition, the ARDL technique generally provides unbiased estimates of the long-run model and valid t-statistics even when some of the regressors are endogenous (Odhiambo, 2009). The model is as follows:

$$\Delta InOil_t = a_0 + \sum_{i=1}^{n} a_{1i} \Delta InOil_{t-1} + \sum_{i=0}^{n} a_{2i} \Delta InInd_{t-1} + a_3 InOil_{t-1} + a_4 InInd_{t-1} + \mu_t \quad (12)$$

$$\Delta InInd_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} \Delta InInd_{t-1} + \sum_{i=0}^{n} \beta_{2i} \Delta InOil_{t-1} + \beta_3 InInd_{t-1} + \beta_4 InOil_{t-1} + \mu_t \qquad (13)$$

Where *InOil* is the oil price shocks (NOPI); *InInd* is the equity Index (EI) real returns μ is the white noise error term and Δ is the first difference operator. The oil price shock is the dependent variable on the first equation and equity index nominal and real returns as the dependent variable on the second equation. The null hypothesis is stated as no cointegration between the variables, oil price shock and equity markets, with an alternate hypothesis of cointegration between oil price shocks and equity. The hypothesis is stated as:

$$H_0: \; a_3 = a_4 = 0 \qquad (14)$$

Alternate Hypothesis as

$$H_1: \; a_3 \neq a_4 \neq 0 \qquad (15)$$

The null hypothesis is accepted if the *F* statistics is lower than the lower bound value. The alternate hypothesis is accepted if the *F* statistics exceeds the upper critical bounds value. The hypothesis testing of cointegration becomes inconclusive if the *F* statistics falls into the bounds.

3.1.4 Granger non-causality tests

Should there be a long-run relationship between oil price shocks and indices measured, then the Granger non-causality test is done to determine the direction of the causality shock. The Granger causality tests that are conducted at a first difference through vector auto regression (VAR) might be misleading if cointegration is detected. Therefore, an inclusion of error correction term VAR method will assist in capturing the direction of the long-run relationship. By including the lagged error-correction term, the long-run information lost through differencing is reintroduced in a statistically acceptable way (Shahbaz & Feridum, 2012; Odhiambo, 2009).

Causality test between oil price shocks (NOIP) and equity index:

$$\Delta InOil_t = a_0 + \sum_{i=1}^{n} a_{1i} \Delta InOil_{t-i} + \sum_{i=0}^{n} a_{2i} \Delta InInd_{t-i} + ECM_{t-1} + \mu_t \qquad (16)$$

$$\Delta InInd_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} \Delta InInd_{t-i} + \sum_{i=0}^{n} \beta_{2i} \Delta InOil_{t-i} + ECM_{t-1} + \mu_t \qquad (17)$$

where ECM_{t-1} is the lagged error correction term obtained from the long-run relationship. The direction of the causality is determined by the *F* statistics and the lagged error term. The *t* statistics on the coefficient of the lagged error correction term represents the long-run causal relationship while the *F* statistics on the explanatory variable represent the short-run causal relationship (Odhiambo, 2009).

3.1.5 Bivariate GARCH

The time varying Baba–Engle–Kraft–Kroner (BEKK) bivariate GARCH is used to estimate the volatility spillovers between oil price shocks and the equity markets and the conditional variance between these markets. The BEKK GARCH model allows capturing the dynamics of variance and covariance overtime (Chevallier, 2012). McAleer, Chan, Hoti, and Lieberman (2008) add that the BEKK GARCH model the conditional covariance so that the conditional correlations are time varying. The model is presented as follows (Li, 2015):

$$H_t = \Omega^{'}\Omega + B^{'} H_{t-1} B + A^{'} \varepsilon_{t-1}^{'} \varepsilon_{t-1} A, \qquad (18)$$

where

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}; \Omega = \begin{bmatrix} \omega_{11} & 0 \\ \omega_{21} & \omega_{22} \end{bmatrix}; A = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, B = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \text{and } \varepsilon_{1t,2t} = \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix}$$

A matrix measures the ARCH effects while B matrix measures the GARCH effects. The above is equivalent to:

$$h_{11,t} = \omega^2_{11} + \beta^2_{11}h_{11,t-1} + 2\beta_{11}\beta_{21}h_{12,t-1} + \beta^2_{21}h_{22,t-1} + \alpha^2_{11}\varepsilon^2_{1,t-1} + 2\alpha_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha^2_{21}\varepsilon^2_{2,t-1} + 2\alpha_{11}\alpha_{21}h_{12,t-1} \quad (19)$$

$$h_{22,t} = \omega^2_{21} + \omega^2_{22} + \beta^2_{12}h_{11,t-1} + 2\beta_{12}\beta_{22}h_{12,t-1}\beta^2_{22}h_{22,t-1} + \alpha^2_{12}\varepsilon^2_{1,t-1} + 2\alpha_{12}\alpha_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha^2_{22}\varepsilon^2_{2,t-1} \quad (20)$$

$$h_{12,t} = \omega_{11}\omega_{21} + \beta_{11}\beta_{12}h_{11,t-1} + (\beta_{12}\beta_{21} + \beta_{11}\beta_{22})h_{12,t-1} + \beta_{21}\beta_{22}h_{22,t-1} + \alpha_{11}\alpha_{12}\varepsilon^2_{1,t-1} + (\alpha_{21}\alpha_{12} + \alpha_{11}\alpha_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{21}\alpha_{22}\varepsilon^2_{2,t-1} \quad (21)$$

$h_{11,t}$ is the oil price real returns' conditional variance and $h_{22,t}$ is the stock index real returns' conditional variance, which measures direct cross volatility (cross GARCH effects) between oil and index with the coefficients of β^2_{21} and β^2_{12} in the models derived from equations 19 and 20 respectively. In addition, $h_{12,t}$ is the covariance between oil price and stock index returns.

$\varepsilon_{1t,2t}$ are the conditional residuals. The $\varepsilon^2_{2,t-1}$ and $\varepsilon^2_{1,t-1}$ capture the volatility spillover or shocks (cross ARCH effects) between oil price and stock index with the coefficients of α^2_{21} and α^2_{12} in the models from equations 19 and 20 respectively. $\beta^2_{11}h_{11,t-1}$ and $\beta^2_{12}h_{11,t-1}$ are the variables' own past volatilities for oil returns and index returns respectively (GARCH effects). $\alpha^2_{11}\varepsilon^2_{1,t-1}$ and $\alpha^2_{12}\varepsilon^2_{1,t-1}$ measure the variables' own past shocks or news transmission (ARCH effects) for oil and index returns respectively.

The bivariate GARCH model of the above specifications is estimated by the maximum log-likelihood function, presented as (Li, 2015):

$$L(\theta) = -TIn(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(In\,|\,H_t\,| + \varepsilon'_t\,H_t^{-1}\varepsilon_t\right) \quad (22)$$

Where *T* is the number of observations and θ is the parameter vector to be estimated.

CHAPTER 4

4.1 Presentation of results

4.1.1 Auto Regressive distributed lag (ARDL) test results

ARDL modelling does not require unit root testing. However, it is necessary to conduct unit root testing to ascertain than variables are not integrated of order 2 {*I*(2)}, as the model assumes variables are either at level (*I*(0) or first difference [*I*(1)]. The computed *F* statistics on *I* (2) will not be valid (Odhiambo, 2010). Testing for stationarity is also critical to avoid spurious regressions for other regression estimations.

Table 2 ADF and KPSS tests output – levels of variables

Variable		ADF				KPSS		
lnOil	t stats	1%	5%	10%	t stats	1%	5%	10%
NOIP	-2.7945***	-3.4913	-2.8882	-2.5810	0.2215*	0.7390	0.4630	0.3470
lnInd								
BGSMDCᵼ	-6.9803*	-3.4897	-2.8874	-2.5807	0.0982*	0.7390	0.4630	0.3470
EGX30ᵼ	-9.3433*	-3.4897	-2.8874	-2.5807	0.0627*	0.7390	0.4630	0.3470
SEMDEXᵼ	-7.9460*	-3.4897	-2.8874	-2.5807	0.0633*	0.7390	0.4630	0.3470
MOSEMDXᵼ	-10.0865*	-3.4897	-2.8874	-2.5807	0.0880*	0.7390	0.4630	0.3470
MSCIᵼ	-8.6975*	-3.4897	-2.8874	-2.5806	0.1375*	0.7390	0.4630	0.3470
FTN098ᵼ	-9.6801*	-3.4897	-2.8874	-2.5806	0.0702*	0.7390	0.4630	0.3470
NGSEIDXᵼ	-9.5058*	-3.4897	-2.8874	-2.5806	0.1164*	0.7390	0.4630	0.3470
JALSHᵼ	-10.9761*	-3.4897	-2.8874	-2.5806	0.1089*	0.7390	0.4630	0.3470
DARSDEIᵼ	-9.5025*	-3.4897	-2.8874	-2.5806	0.3520*	0.7390	0.4630	0.3470
NSEASIᵼ	-8.6662*	-3.4992	-2.8916	-2.5828	0.1667*	0.7390	0.4630	0.3470
GGSECIᵼ	-4.6714*	-3.5316	-2.9055	-2.5903	0.3399*	0.7390	0.4630	0.3470
TUNINDEXᵼ	-9.6268*	-3.4897	-2.8874	-2.5806	0.1536*	0.7390	0.4630	0.3470

*, **, *** denote statistical significance at the 1%, 5%and10%levels, respectively.ᵼ denotes real index returns.

Table 2 above shows the results of the variables (NOIP and Indices) tested for stationarity at level *I*(0). Unit root tests are done with an intercept. The KPSS' null hypothesis of a series being stationary is accepted on all the variables at 1% statistical significance. Furthermore, for ADF null hypothesis of a unit root is rejected at 10% significance for the NOPI variable and at 1% significance on all other variables.

Akaike information criterion (AIC) and Schwartz Criterion (SC) obtained the order of the lags (maximum of 4 lags). Stability diagnostics' was tested with cumulative sums (CUSUM) tests on all the estimated models for ARDL *F* bound testing (see figure 16 and 17 for CUSUM tests results). In addition, all estimated models were tested for serial auto correlation on the residuals using the Breusch-Godfrey Serial Correlation LM Test. The

Breusch-Godfrey Serial Correlation LM test (LM (χ^2) is preferred to the DW as the variables have the presence of lagged dependent variable. The Breusch-Godfrey Serial Correlation LM Test ((LM (χ^2) results are presented in Table 3 below. These tests were performed after the stationarity tests and the estimated ARDL *F* bound testing to confirm the stability of the estimated model within the sampled period and to ascertain that these models were clear of autocorrelation in the residuals. Detection of autocorrelation and instability on the estimated model may result in biased and spurious estimations. The CUSUM tests plot the cumulative sums with the 5% critical bounds are presented in Figure 17, with NOPI as a dependent variable and Figure 18 with the index as a dependent variable.

The CUSUM tests show stability if the cumulative sums are not outside the 5% critical lines (Ibrahiem, 2015). Figure 17 and Figure 18 above show that the cumulative sums for estimated model are all within the 5% critical lines for NOPI and indices as dependent variables.

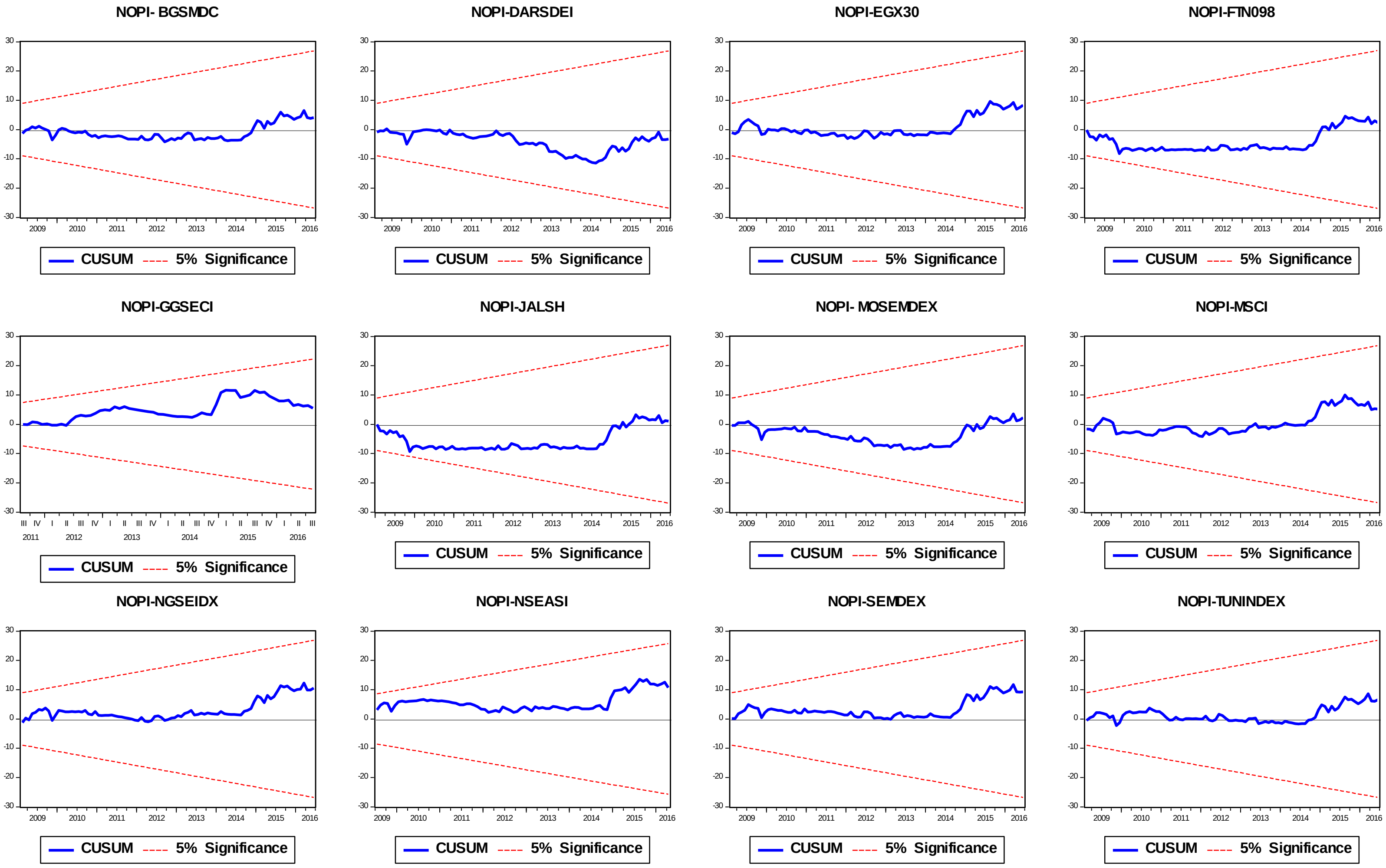

Figure 17 CUSUM tests with NOPI as dependant variable

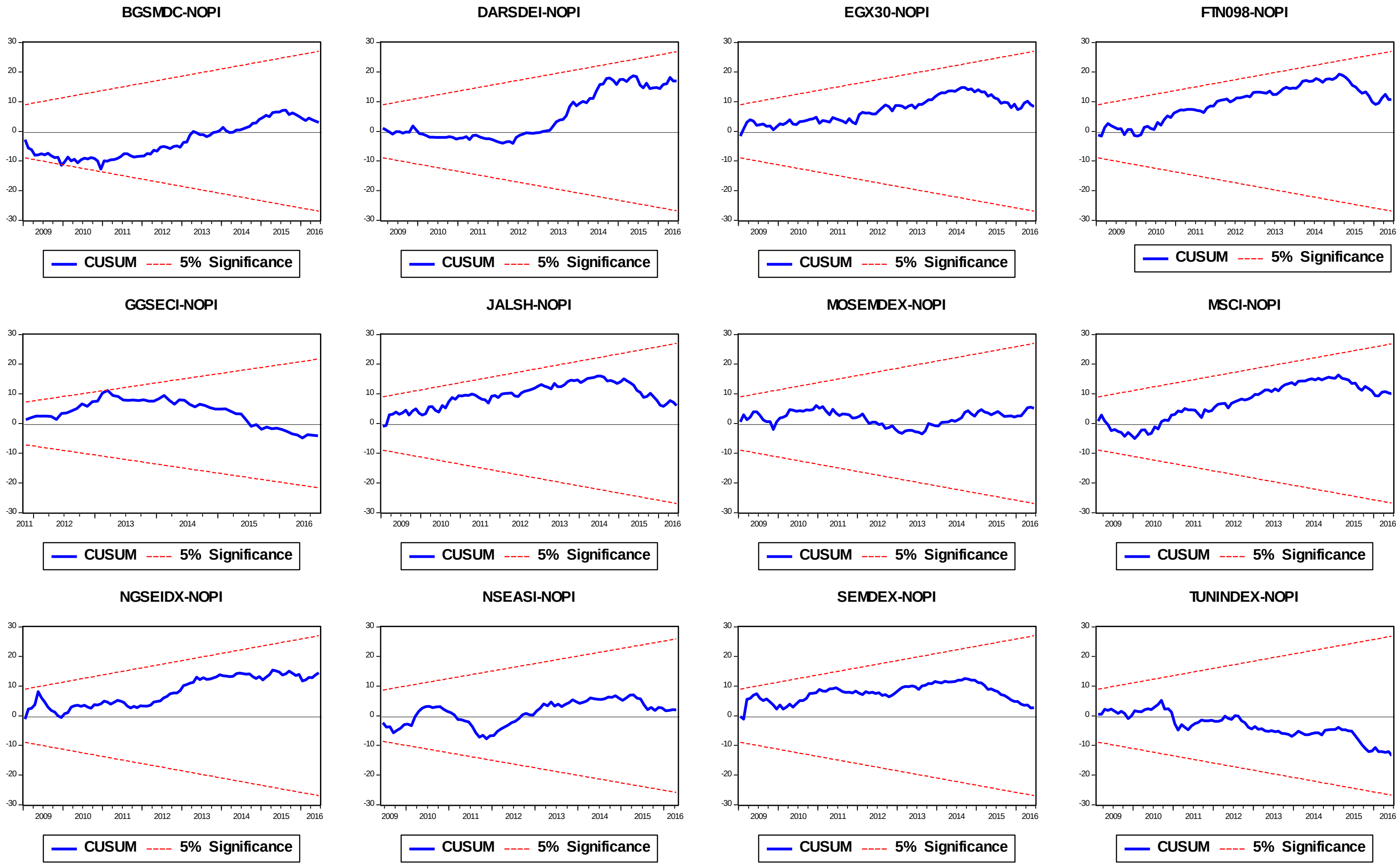

Figure 18 CUSUM tests with index as dependent variable

Table 3 below depicts the ARDL *F* bounds test results.

Table 3 Bounds *F*-test for cointergration

Dependent variable	Function	F-test statistics	LM(χ^2)
Botswana			
NOPI	NOPI(BGSMDCɨ)	2.3749	0.2349
BGSMDCɨ	BGSMDCɨ(NOPI)	11.1874*	0.9087
Egypt			
NOPI	NOPI (EGX30ɨ ɨ)	3.1943	0.4188
EGX30ɨ	EGX30ɨ (NOPI)	24.4537*	0.5628
Mauritius			
NOPI	NOPI (SEMDEXɨ)	3.1302	0.1254
SEMDEXɨ	SEMDEXɨ (NOPI)	10.0019*	0.1647
Morocco			
NOPI	NOPI(MOSEMDEXɨ)	3.10236	0.9168
MOSEMDEXɨ	MOSEMDEXɨ(NOPI)	36.0958*	0.2306
Namibia			
NOPI	NOPI (FTN098ɨ)	1.9924	0.1434
FTN098ɨ	FTN098ɨ (NOPI)	23.5784*	0.8731
Nigeria			
NOPI	NOPI (NGSEIDXɨ)	3.6442***	0.2333
NGSEIDXɨ	NGSEIDXɨ (NOPI)	32.3036*	0.5949
South Africa			
NOPI	NOPI (JALSHɨ)	2.292148	0.2234
JALSHɨ	JALSHɨ (NOPI)	12.5749*	
Tanzania			
NOPI	NOPI (DARSDEIɨ)	2.5693	0.1673
DARSDEIɨ	DARSDEIɨ (NOPI)	30.1517*	0.6418
Kenya			
NOPI	NOPI (NSEASIɨ)	2.4414	0.2605
NSEASIɨ	NSEASIɨ (NOPI)	7.026442*	0.4384
Ghana			
NOPI	NOPI (GGSECIɨ)	0.9238	0.6285
GGSECIɨ	GGSECIɨ (NOPI)	6.6213*	0.6446
Tunisia			
NOPI	NOPI (TUNINDEXɨ)	2.0901	0.2856
TUNINDEXɨ	TUNINDEXɨ (NOPI)	29.0704*	0.8019
World Index			
NOPI	NOPI (MSCIɨ)	6.2915*	0.2674
MSCIɨ	MSCIɨ (NOPI)	21.6229*	0.2690

Asymptotic critical values	**1%**		**5%**		**10%**	
	***I*(0)**	***I*(1)**	***I*(0)**	***I*(1)**	***I*(0)**	***I*(1)**
Asymptotic critical values	**6.027**	**6.760**	**4.090**	**4.663**	**3.303**	**3.797**

*, **, *** denote statistical significance at the 1%, 5%and 10% levels, respectively. Asymptotic critical value bound tests are obtained from Odhiambo (2009:621). ɨ denotes real index returns.

The ARDL *F* bound statistic was found to be lower than the asymptotic values at 10% as presented in Table 3 above. This confirms a long run relationship between variables of interest, in this case, NOPI and stock index. Using the AIC, lag 4 and lag 2 are the best optimal lags for estimating parsimonious models as specified in equations 12 and 13 respectively. The results support a null hypothesis of no long run relationship (no cointegration) when NOPI is a dependent variable in all stock indices except for MSCI and Nigeria's NGSEIDX index, as specified by the model in equation 12. Using NOPI as dependent variable with MSCI and NGSEIDX as independent variables, the null hypotheses of no long run relationship is rejected. The null hypothesis of no long run relationship is accepted when all indices (except for MSCI and NGSEIDX) are used as dependent variable, as specified by the model in equation 13. This relationship implies that there is unique cointegration vector in the models specified in equation 12 and 13, except when variables MSCI and NGSEIDX are used.

About 59.28% (6.81% is from energy companies) of the MSCI constituents is from the United States (US) companies, while 6.63% and 9.18% comes from UK and Japanese companies respectively (MSCI, 2016). This may be an indicator of the reverse or non-unique cointegration for the world index as specified in Table 4. Furthermore, the reverse cointegration is also not surprising for Nigeria because its value of petroleum exports amounted to $ 41.818 billion in 2015 and has proven oil reserves of about 37 million barrels (OPEC, 2016). Economic developments in large oil exporting countries (typically reflected in stock market indices) have the potential to impact oil markets contributing to oil shocks.

Malik and Hammoudeh (2007) posit that volatility from USto Gulf Cooperation Council (GCC) is through the capital flows. This is driven by GCC[6] investors placing large amounts of petrodollar in the US capital markets exceeding $800 billion used as a cross market hedging and for permanent parking spot for safety. In addition, the oil prices are traded in US currency (US dollar). As a result, the crude oil will be adversely affected by the movement of the US dollar exchange rate, and the volatility of the US exchange rate will render the international purchasing power of crude exporting countries to be unpredictable (Zhang, Fan, Tsai & Wei, 2008). In fact, Zhang et al.'s (2008) empirical findings attribute the soaring oil prices (oil price shocks) to the US dollar depreciation. Furthermore, the US itself is a major oil importer and exporter. In 2015 alone, the US imported 9.4 million

[6] The GCC region is a massive driver of the oil market economy. According to data from OPEC (2016) based on the year 2015, Saudi Arabia exports $157,962 million worth of oil, with reserves amounting to 266,455 million barrels. United Arab Emirates and Kuwait exports $52,369 million and $48,782 million worth of oil respectively, with reserves of 97,800 and 101,500 million barrels for United Arab Emirates and Kuwait respectively.

barrels per day from 88 countries around the globe and exported 4.7 million barrels per of petroleum to 147 countries (EIA, 2017).

The long-run relationship has been tested and only confirmed when the index is a dependent variable in most of the estimated models (MSCI, NGSEIDX and NOPI). This suggests long-run relationship when either of the variables are dependent variables), which suggests that there must be a direction of causality between NOPI and index variables. The next step is to test the direction of the causality in all variables by incorporating the lagged error-correction term into the relevant cointegrating vectors (see equations 16 and 17). Table 5 below depicts the Granger non-causality tests of variables with long-run relationships (cointegration). The results shown are only for the tests that reject the null hypothesis of no long-run relationship as in presented in Table 3.

The long-run causality is examined through the significance of the coefficient of the lagged error correction term, which must be negative and statistically significant. Conversely, the short run causality is examined through the joint significance of the lagged differences of the independent variable using the Wald test, which must be statistically significant (Odhiambo, 2010).

The error correction term restricts the long-run behaviour of the endogenous variables to converge to their cointegration relationship as it has the cointegration built into the specification, and also allowing for short-run adjustment dynamics. The long-run equilibrium is gradually corrected through the series of partial short-run adjustment (Eviews8, 2014). Furthermore, Brooks (2014) mention that the error correction term describes the speed of adjustment back to equilibrium, and its strict definition is that it measures the proportion of last period’s equilibrium error for which it is corrected.

Table 4 shows the long-and-short run causality tests with variable NOPI is a dependent variable and an index as a dependent in equations 16 and 17 respectively. The results suggest that there is a long-and short-run causality from NOPI to BGSMDC. This is confirmed by the lagged error correction term that is negative and highly statistically significant at 1% and the *F* statistics of BGSMDC function, which is significant at 5%. In contrast, EGX30 is showing only long-run causality from NOPI as the error correction term is also negative and highly significant at 1%.

The bidirectional long-run causality is evident in Nigeria, with the error correction term negative and highly significant at 1%. This can be attributed to the fact that Nigeria is an oil exporter. According to CNBC Africa (2016), Nigeria produced 2.2 million barrels a day in 2016, which accounts for around 10% of Nigeria's GDP.

Table 4 Granger causality tests

Dependent Variable	Causal Flow	F- statistics	t- stats(ECM)	ECM$_{t-1}$
Botswana				
BGSMDCł	NOPI → BGSMDCł	3.3899[0.0110]**	-7.3573	-0.6359*
Egypt				
EGX30ł	NOPI → EGX30ł	1.3942[0.2526]	-8.6462	-0.8447*
Mauritius				
SEMDEXł	NOPI → SEMDEXł	1.6530[0.1964]	-7.9695	-0.7559*
Morocco				
MOSEMDEXł	NOPI→MOSEMDEXł	2.2821[0.1071]	-10.5047	-0.9876*
World Index				
MSCIł	NOPI → MSCIł	1.1330[0.3260]	-8.1305	-0.8039*
NOPI	MSCIł → NOPI	6.0486[0.0002]*	-4.2079	-0.0649*
Namibia				
FTN098ł	NOPI → FTN098ł	4.0448[0.0203]**	-8.4901	-0.8424*
Nigeria				
NGSEIDXł	NOPI → NGSEIDXł	1.5974[0.2073]	-9.9378	-0.9816*
NOPI	NGSEIDXł → NOPI	1.3626[0.2524]	-3.5687	-0.1047*
South Africa				
JALSHł	NOPI → JALSHł	3.9569[0.0220]**	-9.1865	-0.9446*
Tanzania				
DARSDEIł	NOPI → DARSDEIł	2.7212[0.0704]***	-9.8099	-0.9412*
Kenya				
NSEASIł	NOPI → NSEASIł	1.4285[0.2317]	-4.0464	-0.6019*
Ghana				
GGSECIł	NOPI → GGSECIł	0.8851[0.4180]	-4.5306	-0.4953*
Tunisia				
TUNINDEXł	NOPI → TUNINDEXł	0.7923[0.4555]	-9.4272	-0.9138*

This table reports results of the Granger causality tests in which the hypothesis of no causality is rejected. *, **, *** denote statistical significance at the 1%, 5%and 10% levels, respectively. ł denotes real index returns. *p*-values are presented in square brackets.

FTN098, JALSH, DARSDEI, and MSCI confirm long-and short-run causality, with the error correction term negative and highly significant at 1%. In contrast, the *F* statistics for short-run causality is significant at 10% for DARSDEI, 5% for JALSH and FTN098, and highly significant at 1% for MSCI. Mauritian SEMDEX confirms causality only in the long-run, with a highly negative significant error correction term at 1% and the non-significant *F*-statistics. NSEASI, GGSECI, MOSEMDEX, and TUNINDEX complete the long-run causality from NOPI, with the error correction term negative and highly significant at 1%.

The highest error correction term is -0.9876 for Morocco's MOSEMDEX, which indicates that a deviation from the long-run equilibrium following a short-run shock is corrected by 98.76% after one month. The lowest error correction term of -0.1047 suggests a deviation from the long-run equilibrium following a short-run shock corrected by 10.47% from NGSEIDX to NOPI after one month.

These findings are consistent with the findings by Narayan and Narayan (2010) in the emerging Vietnamese economy in which they found the long-run relationship between stock and oil prices. Furthermore, Gomes and Chaibi (2014) also found that oil price shocks Granger cause changes in the stock market returns in emerging markets of Jordan, Ukraine, Lebanon, United Arab Emirates, Oman, Saudi Arabia and Qatar. In addition, the causality findings for most of the oil importing African markets in this study is consistent with analysis from other empirical findings in similar emerging markets. Dagher and Hariri (2013) empirically finds that oil prices are Granger causing stock prices, but no evidence of the opposite relationship in the Lebanese stock market.

Raza et al (2016) found oil prices have an impact on stock markets in Brazil, Russia, India, China, Mexico, Malaysia, Thailand, Chile and Indonesia. However, the results slightly contrast with a study by Kapusuzoglo (2011), which found a one-way causality relationship from Istanbul Stock Exchange indices to oil price.

4.2 GARCH (1, 1) estimated results

Correlation gives an indication on how the markets co-vary. This is important for this study as it gives an indication on markets movements and how they co-vary in comparison to oil and World Index (MSCI) returns. This information is also important from an investor's perspective, as it gives an opportunity for diversification and hedging strategies. Table 5 below shows the correlation results. Strong correlation is observed between South Africa and World index at 67.78%. This might be due to the accessibility of Johannesburg Stock Exchange to international investors as South Africa is more integrated into the world's financial and commodity markets than other African markets or potentially its higher liquidity as compared to other African markets.

As expected, Namibian stock market has a strong, positive correlation with South Africa and World Index at 82.60% and 60.90% respectively. There is a significant positive correlation between Brent crude returns and South Africa at 42.53%, Namibia at 44.10% and world index at 44.71%. Other African markets show weak correlation with both Brent crude and World Index (MSCI), except for Nigeria, which is slightly higher at 27.88%. There is a negative correlation between the World Index and Tunisia at -17.46%. Lastly, small negative correlations are observed between Brent crude, with Mauritius and Tunisia at -4.08% and -3.09% respectively.

Table 5 Correlation matric for index and Brent crude excess returns

	Brent	Botswana	Ghana	Kenya	Egypt	Mauritius	Morocco	Namibia	Nigeria	S. Africa	Tanzania	Tunisia	World
Brent	1.0000												
Botswana	0.0740	1.0000											
Ghana	0.1295	0.4058*	1.0000										
Kenya	0.0896	-0.0226	0.2785**	1.0000									
Egypt	0.1099	-0.1756	-0.0075	0.3570*	1.0000								
Mauritius	-0.0408	0.2210***	0.3913*	0.2528**	-0.1030	1.0000							
Morocco	0.0566	-0.0044	-0.1024	0.1120	0.2299***	-0.0170	1.0000						
Namibia	0.4410*	-0.1638	0.0467	0.2972**	0.4942*	0.0035	0.1402	1.0000					
Nigeria	0.2788**	0.2185***	0.3276*	0.5540*	0.2214***	0.3330*	-0.2297***	0.1403	1.0000				
S. Africa	0.4253*	-0.2108***	0.0049	0.3709*	0.5235*	-0.0229	0.0799	0.8260*	0.2788**	1.0000			
Tanzania	0.1843	0.0017	0.0789	0.3602*	0.2698**	0.0742	0.4151*	0.1431	0.1219	0.133847	1.0000		
Tunisia	-0.0309	-0.0205	-0.0657	-0.1613	0.0636	-0.1396	-0.1175	-0.0050	- 0.2730**	-0.0124	0.0781	1.0000	
World	0.4471*	0.1308	0.1684	0.4284*	0.4470*	0.1019	0.0815	0.6090*	0.3124*	0.6778*	0.0974	-0.1746	1.0000

*, **, *** denote statistical significance at the 1%, 5% and 10% levels respectively.

Before estimating the GARCH (1, 1) model, the first step is to test for the ARCH effects in the mean equation (Hegerty, 2016) of the oil and index returns. The finding of ARCH effects with a statistical significance of 10% or less will justify the use of the nonlinear model like the GARCH. Table 6 presents the results. The null hypothesis of no ARCH effects is rejected for Brent oil returns, world index, and Morocco at a statistical significance of 5% and some of the stock indices at a statistical significance of 1% (South Africa, Nigeria, Mauritius, and Namibia).

Table 6 ARCH effects tests results on excess returns on the mean equation

	Brent	Botswana	Egypt	Mauritius	Morocco	Namibia	Nigeria	S.Africa	Tanzania	Kenya	Ghana	Tunisia	World
ARCH(12)	0.0831***	0.1421	0.9308	0.0000*	0.0478**	0.0000*	0.0037*	0.0005*	0.9988	0.0000*	0.3269	0.5216	0.0244**

This table reports *p*-values of the ARCH tests effects. *, **, *** denote statistical significance at the 1%, 5% and 10% levels respectively.

The GARCH (1, 1) is the most appropriate for volatility estimations as it avoids overfitting and it is parsimonious (Brooks, 2014). Brooks (2014) adds that GARCH (1, 1) is sufficient for capturing the volatility clustering within a time series data. After estimating the GARCH (1, 1), the autocorrelation is examined using the Correlogram–Q-statistics and Correlogram squared residuals. If the resulting estimations have no autocorrelation in the residuals using Correlogram–Q-statistics and Correlogram squared residuals tests, then this suggests that the mean and variance equations are correctly specified, respectively.

The null hypothesis of no serial correlation using both Correlogram–Q-statistics and Correlogram squared residuals is not rejected for all estimations, except for Botswana, Mauritius[7], Kenya, and Ghana. In order to eliminate serial correlation, the models found with serial correlation on residuals are estimated with the auto regressive (AR) term in the mean equation (Urquhart & McGroarty, 2016). In addition, the null hypothesis of no ARCH up to the 12 lags is tested on the estimations using the residual diagnostics ARCH LM test. These ARCH LM tests are important as the results give an indication if the variance equations are correctly specified. The results suggest no ARCH up to 12 lags in all estimations.

The GARCH (1,1) results in Table 7 suggest that the markets returns' own past volatility and its own past shocks contribute to the current volatility. However, Egypt is an exception, with the coefficient of GARCH effects (own past volatility) not significant and for Tunisia, suggesting that its own ARCH effects or shocks not directly contributing to current volatility, as the coefficient of b_1 is not statistically significant. Ghana's GARCH (1,1) estimation show insignificant GARCH and ARCH effects, but the AR variable is statistically significant at 1%. There is a high volatility persistence observed, with Brent crude being the highest closest to 1, suggesting volatile fluctuations in the future. Egypt's and Ghana's volatility persistence are low at 0.5098 and 0.5000 respectively.

[7] To deal with autocorrelation on Mauritius (SEMDEX) when estimating the GARCH(1,1), the Box-Jenkins (Brooks, 2014) method of estimating optimal ARMA model was applied using the AIC, and the most optimal parsimonious model was found to be ARMA (2,2). Autocorrelation was totally cleared on the variance equation from lags 1 to 4 and from lags 16 to 36. Serial correlation was cleared on the mean equation from lags 11 to 36.

Table 7 GARCH (1, 1) estimation results on excess returns

	Brent	Botswana	Egypt	Mauritius	Morocco	Namibia	Nigeria	S. Africa	Tanzania	Kenya	Ghana	Tunisia	World
μ_i	0.0036	0.0034	-0.0046	-0.0004	0.0877	0.0038	0.0038	0.0090*	0.3276**	0.0108	0.5869	0.6841***	0.0043
	(0.4618)	(0.9763)	(-0.5083)	(-0.1876)	(0.2633)	(0.7686)	(0.4822)	(3.0103)	(2.5299)	(1.2908)	(0.6085)	(1.8743)	(0.9410)
AR(1)		0.4052*		0.6378						0.1355	0.5103*		
		(32.8829)		(1.5817)						(0.8532)	(3.6836)		
b_0	0.0004	3.75E-06	0.0049***	8.17E-06	0.1816	0.0002	0.0006	0.0002	0.2171*	0.0003	6.0434	1.8476	0.0002
	(1.0540)	(0.5268)	(1.8945)	(0.4552)	(0.6057)	(1.1168)	(1.1817)	(0.9960)	(10.8408)	(1.2933)	(0.6241)	(1.3216)	(1.1211)
b_1	0.3196*	-0.0619*	0.3865*	0.1859***	-0.0980***	0.2087**	0.2067***	0.3503***	-0.0363*	0.3461**	0.1889	0.1423	0.2304*
	(3.3504)	(-3.1129)	(2.6870)	(1.8487)	(-1.6733)	(1.9690)	(1.8270)	(1.8412)	(-7.1357)	(1.9842)	(0.4800)	(1.4659)	(2.5904)
b_2	0.6904*	1.0523*	0.1233	0.7928*	1.0878*	0.7446*	0.7103*	0.6003*	1.0235*	0.5868*	0.3111	0.7432*	0.6796*
	(8.5250)	(32.1486)	(0.4458)	(9.4028)	(21.2456)	(6.1990)	(4.2337)	(3.3461)	(129.8966)	(3.2244)	(0.3481)	(4.4091)	(4.8821)
$b_1 + b_2$	1.0100	0.9904	0.5098	0,9787	0.9898	0.9533	0.9170	0.9506	0,9872	0,9329	0,5000	0.8855	0.9100
LM(12)a	0.1330	0.6810	0.4510	0.1430	0.2060	0.8250	0.1480	0.9550	0.4600	0.1250	0.9470	0.7620	0.8330
LM Q2(12)[b]	0.7170	0.217	0.9220	0.0600***	0.4630	0.2220	0.3030	0.3330	0.9960	0.3410	0.8720	0.5910	0.8610
ARCH(12)c	0.7762	0.2574	0.9598	0.4864	0.5731	0.3853	0.2461	0.3721	0.9981	0.2277	0.9268	0.6968	0.9231

*, **, *** denote statistical significance at the 1%, 5% and 10% levels respectively. *t* statistics are presented in parentheses(). b_1 is the variable own ARCH effects, b_2 is the variable own GARCH effects. $b_1 + b_2$ is variables' volatility persistence.

4.1.3 Bivariate GARCH test results

Table 8 BEKK GARCH estimation results based on the GARCH (1, 1)

	Botswana	Egypt	Mauritius	Morocco	Namibia	Nigeria	S. Africa	Tanzania	Kenya	Ghana	Tunisia	World
β_{11}^2	0.7082*	0.7022*	0.4586*	0.1365	0.6330*	0.6747*	0.4698*	0.4876*	0.3596***	0.7065*	0.0588	0.4069*
	(6.6035)	(8.7406)	(4.4450)	(0.7782)	(4.7747)	(7.2788)	(5.3865)	(4.1218)	(1.7087)	(8.2386)	(-1.3556)	(4.7597)
β_{12}^2	0.0311***	0.0582	0.0802***	0.0139	0.3586*	0.0403	0.0271***	4.5683**	0.1764**	0.0349	2.8968**	0.1548**
	(1.6972)	(0.6448)	(1.6509)	(0.6186)	(2.8019)	(1.1298)	(1.7050)	(-2.4395)	(2.0088)	(0.9464)	(-2.3932)	(2.2353)
α_{11}^2	0.0884*	0.2882*	0.2548*	0.2894*	0.2549*	0.2734*	0.3132*	0.0651**	0.1815**	0.2357*	0.3434*	0.4093*
	(1.7978)	(-4.2586)	(-4.1554)	(-3.9871)	(3.6899)	(4.5040)	(4.5941)	(-2.0395)	(-2.5774)	(2.8938)	(5.9587)	(-4.2130)
α_{21}^2	0.0311	0.0392	0.0408	0.2379***	0.0806	0.0061	0.0294	0.0000	0.1651	0.0003	0.6629**	0.2543***
	(-0.4949)	(-1.5313)	(-0.5095)	(-1.8477)	(1.5878)	(0.4364)	(-0.7363)	(0.4452)	(-1.3957)	(0.0382)	(-2.1609)	(1.9150)
β_{21}^2	0.1993	0.0689	0.1163	0.9178	0.0050	0.0009	0.4302*	0.0004	0.1842	0.0383	0.1419*	0.4247***
	(0.9327)	(-0.5925)	(0.8616)	(1.0394)	(-0.1766)	(-0.2618)	(2.7156)	(1.4408)	(0.4935)	(0.2131)	(-3.4324)	(1.9375)
β_{22}^2	0.1739***	0.1490	0.0904	0.4139	0.0056	0.5946*	0.3750*	0.0001	0.3400*	0.0477	0.1641*	0.0792
	(1.7403)	(0.7531)	(0.7359)	(1.5465)	(-0.1560)	(3.9693)	(4.0695)	(0.0280)	(-2.6406)	(-0.6608)	(2.9977)	(0.6961)
α_{12}^2	0.0032	0.0202	0.0001	0.0231**	0.0095	0.0801*	0.0032	324.1141*	0.0733**	0.0378*	0.0049***	0.0056
	(0.8165)	(-0.8043)	(-0.5724)	(-2.4735)	(-0.6337)	(2.4353)	(0.9103)	(-3.2026)	(-2.2891)	(-2.8249)	(1.7884)	(0.9254)
α_{22}^2	0.3147*	0.2023*	0.3538*	0.0221	0.1348*	0.0012	0.4175*	0.0466***	0.13469**	0.2781*	0.1092*	0.0001
	(-2.8379)	(-2.6971)	(-3.5693)	(0.9961)	(2.2878)	(-0.1479)	(-4.8949)	(-1.8411)	(-2.2899)	(-4.3616)	(-3.1592)	(-0.0068)
ω_{11}^2	0.0014**	0.0000	0.0001*	26.4166	0.0006**	0.0007***	0.0001	0.0006	0.0023*	6.2119	6.8817	0.0001
	(2.0676)	(-0.0283)	(3.2161)	(-4.0397)	(2.3799)	(1.7082)	(0.2888)	(0.5349)	(-3.0474)	(0.7542)	(-0.5874)	(-0.1702)
ω_{21}^2	0.0004**	0.0044	0.0001	4.5937	0.0003	0.0001	0.0000	5.0766	0.0002	5.5112	0.2339	0.0002
	(-2.3893)	(-0.0279)	(-1.0358)	(1.4522)	(-0.4540)	(-0.7115)	(0.2262)	(-0.5519)	(0.3537)	(-0.4536)	(0.3624)	(0.1947)
ω_{22}^2	0.0000	0.0000	0.0000	0.2379***	0.0000	0.0003**	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000
	(-0.0000)	(-0.0000)	(0.0000)	(-1.8477)	(-0.0000)	(1.9883)	(-0.0000)	(0.0000)	(-0.0000)	(-0.0000)	(-0.0000)	(0.0000)

*, **, *** denote statistical significance at the 1%, 5% and 10% levels respectively. *t* statistics are presented in parentheses(). β_{11}^2 is the oil returns' own GARCH effects, α_{11}^2 is the oil returns own ARCH effects or news and shocks transmission. β_{22}^2 is the index own GARCH effects, α_{22}^2 is the index returns own ARCH effects/news and shock transmission. β_{21}^2 is the direct volatility from index return to oil return. β_{12}^2 is the direct volatility from oil returns to index returns. α_{21}^2 is the news or shock volatility spill over from index return to oil returns. α_{12}^2 is the news or shock volatility spill over from oil returns to index returns.

The evidence of direct cross volatilities from oil price returns to index returns for Botswana, Namibia, South Africa, Tanzania, Kenya, Tunisia, Mauritius and World Index. The evidence is supported by the statistical significant coefficient of β_{12}^{2} in equation 20.

The statistical significance of 10% is observed for Botswana, Mauritius and South Africa. Tanzania, Kenya, Tunisia and World Index have a statistical significance of 5%, while Namibia's statistical significance is at 1%. Bouri (2015b) found a similar finding, with only oil transmitting its volatility to the Tunisian stock market at the 10% significance level. Furthermore, there is evidence of transmission shock spill over or news from oil to index returns for Morocco at statistical significance of α_{12}^{2} at 5% with Nigeria, Ghana, and Tanzania at 1% statistical significance, Tunisia at 10% statistical significance and Kenya at 5% significance level in equation 20. The results are similar to Lin, et al.'s (2014) empirical findings, which suggest an oil spillover from oil to stock in both the Ghanaians and Nigerian markets at 1% significance.

As expected, there is a direct volatility transmission from world index[8] to oil. This evidence is supported by the 10% statistically significant coefficient of β_{21}^{2} in equation 19. Malik and Hammoudeh (2007) found oil market being affected by the US equity market and the US equity market being indirectly affected by the oil market volatility. Unexpectedly, the β_{21}^{2} coefficient is statistically significant at 1% for South Africa and Tunisia and α_{21}^{2} is statistically significant for Morocco and Tunisia. Gomes and Chaibi (2014) reported a similar finding in which Jordan was significant at 10% for the β_{21}^{2} coefficient. Furthermore, Bouri (2015b) also found bidirectional volatility between oil and index in the Jordanian markets. Furthermore, Gomes and Chaibi (2014) suggest that their findings might be due geographical area of Jordan, which is close to oil producing countries like Saudi Arabia. As a result, co-movements might induce the Jordanian markets between Jordanian and Saudi Arabian markets, which may appear as spillovers. This could be the same for Tunisia and Morocco, due to their proximity to Libya and Algeria. There could also be potential spillovers or co-movements between these markets. Libya is a major oil producing country, with proven oil reserves of 48,363 million barrels and production of 1.65 million barrels per day in 2015, and further exporting oil worth $4,975 million (OPEC, 2016). In addition, Algeria has proven oil reserves of 12, 2 million barrels, while exporting oil worth $21,751 million in 2015 (OPEC, 2016).

[8] The world MSCI index constitutes 59.28% (6.81% is from energy companies) of US companies, while 6.63% and 9.18% comes from UK and Japanese companies respectively (MSCI, 2016).

Libya has been a member of OPEC since 1962, while Algeria has been a member of OPEC since 1969 (OPEC, 2016). With these substantial oil production capacity and reserves, the volatile Libyan markets can potentially spillover into the oil market and increase volatility.

Bouri (2015b) attributes these findings to high liquidity and diversified structure of the Jordanian market, which will attract investors when markets are stable and less volatile. However, the same investors will pull out in times of uncertainty driven by the financial crisis and higher volatility. Moroccan and Tunisian markets have much more liquidity than that of Jordan (Bouri, 2015b). According to Bouri (2015b), high liquid and diversified markets may probably drive bidirectional volatility between oil and stock markets.

This suggestion could be similar to that of South Africa, which is arguably the most diversified and liquid market within the African markets context. The high correlation between South African and world index can also induce co-movements which may also appear as spillovers. Interestingly, Mensah and Alagidede's (2017) empirical study found dependence structure between the South African and advanced stock markets, but not for other African markets. This indicates that the South African market is not immune to spillovers, and supported strong correlation between South Africa and more advanced stock markets in the form of the US and UK.

Soytas and Oran (2011) unexpectedly found that there is a unidirectional causality from the Turkish electricity index returns to oil returns. These empirical findings are interesting because just like South Africa, the World Bank regards Turkey as an upper middle income economy. The authors suggest the findings may be that the Turkish energy companies may be following similar dynamics with larger global companies that could impact oil markets. Further empirical studies are needed to investigate and expand on potentially spillovers from South Africa to Brent crude, to figure out if the spillover is due to potential co-movements with major world markets and seen as spill over.

The cross shock and volatility transmission are not significant for Egypt, but past own GARCH and ARCH effects for oil and past ARCH effects for Egypt are statistically significant for these indices. This can be attributed to low dominance of the banking or financial and development sectors in these markets. This may suggest that oil price shocks may not be easily transmitted in their respective markets (Bouri, 2015b). The Wald test is used for further volatility spillover tests between oil price returns (OP) and the stock index (EI) returns.

Examining the volatility spillover effect that the index has on the oil market is equivalent to testing whether β_{21} and α_{21} is equal to zero (Li, 2015). Failure to reject the null hypothesis, $H_0 : \beta_{21} = \alpha_{21} = 0$ suggests that there is no volatility spillover from index to oil market. Similarly, to examine the volatility spillover effect that the oil has on the index market is equivalent to testing whether β_{12} and α_{12} is equal to zero (Li, 2015). Again, failure to reject the null hypothesis of H_0 : $\beta_{12} = \alpha_{12} = 0$ indicates that there is no volatility spillover from oil to index market. The null hypothesis of no volatility spillover between oil and index markets is examined by testing the restriction: $\beta_{21} = \alpha_{21} = \beta_{12} = \alpha_{12} = 0$. Results are displayed in the Table 9 below.

Table 9 Bivariate GARCH Wald test

χ	Botswana	Egypt	Mauritius	Morocco	Namibia	Nigeria	S. Africa	Tanzania	Kenya	Ghana	Tunisia	World
ϕ	0.68814[0.7089]	2.4103[0.2996]	1.9395[0.3792]	3.8304[0.1473]	3.0583[0.2167]	0.3500[0.8394]	12.7445[0.0017]*	2.5460[0.2800]	2.6436[0.2667]	0.0457[0.9774]	5.7635[0.0560]***	5.9112[0.0520]***
φ	3.4917[0.1745]	1.1865[0.5525]	3.61051[0.1644]	7.6264[0.0221]**	8.5768[0.0137]**	6.5497[0.0378]**	4.8625[0.0879]***	16.9311[0.0002]*	10.7603[0.0046]*	8.6514[0.0132]**	13.0539[0.0015]*	5.5667[0.0618]***
γ	5.3936[0.2492]	4.8408[0.3040]	4.4802[0.3449]	12.8654[0.0120]**	20.3864[0.0004]*	7.3834[0.1170]	16.3426[0.0026]*	48.8351[0.0000]*	16.7263[0.0022]*	8.9315[0.0628]***	985.0197[0.0000]*	28.1596[0.0000]*
Spill over	------	-------	----------	***OP➔ EI***	***OP➔ EI***	***OP➔ EI***	***OP⇔ EI***	***OP➔ EI***	***OP➔ EI***	***OP ➔ EI***	***OP ⇔ EI***	***OP ⇔ EI***

*, **, and *** denotes statistical significance of 1%, 5% and 10% respectively. OP is the oil price movement and EI is the equity or stock index. χ is chi-square value per equity market of the countries measured. ϕ denotes the null hypothesis of no volatility spill over from stock index to oil price in the form of $H_0 : \beta_{21} = \alpha_{21} = 0$. φ denotes the null hypothesis of no volatility spill over from oil price to stock index in the form of $H_0 : \beta_{12} = \alpha_{12} = 0$. γ denotes the null hypothesis of no volatility spill over between the oil price and stock index (and vice versa) in the form of $H_0 : \beta_{21} = \alpha_{21} = \beta_{12} = \alpha_{12} = 0$. ➔ denotes the direction of the volatility spill over from oil price to index. ⇔ denotes the bidirectional volatility spill over between oil price and stock index.

The bivariate GARCH Wald tests results suggest a spillover from oil returns to most of the African equity markets (Morocco, Namibia, Nigeria, Tanzania, Kenya, South Africa, Tunisia, and Ghana). Again, the Wald test indicates a bidirectional spill over between oil returns and equity index for South Africa and Tunisia. As expected, the bidirectional spillover is observed between the world index and oil returns movements. Lastly, the conditional correlation between oil and stock index is examined. The figure below depicts the conditional correlations between oil and multiple indices.

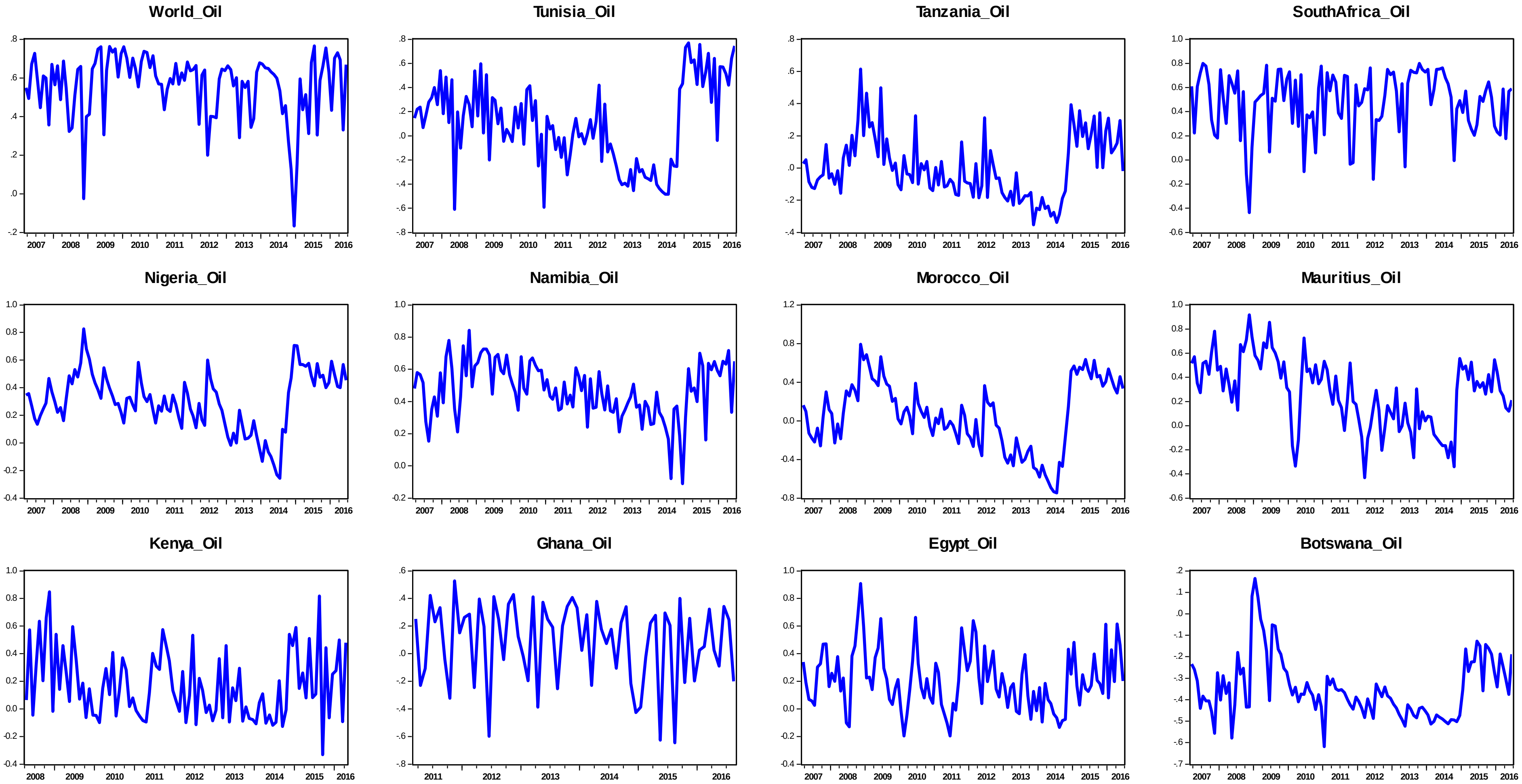

Figure 19 Conditional correlation graphs between stock index and Brent crude oil

The conditional correlations vary between the positive and negative ranges. Botswana and oil conditional correlation is [0.16, -0.62], while Egypt, Ghana and Kenya is [0.91, -0.20], [0.53, -0.65] and [0.85, -0.33] respectively. The other index markets' conditional correlation ranges with Brent crude oil prices are as follows: Morocco at [0.79, -0.74], Mauritius range at [0.92, -0.43], Namibia range at [0.84, -0.11], Nigeria range at [0.83,-0.26], South Africa range at [0.80, -0.44].Tanzania range at [0.62, -0.35], Tunisia range at [0.77, 0.61] and World Index range at [0.76 and -0.17].

Overall, the results suggests a unidirectional direct volatility spillover from oil returns to Botswana, Namibia, Tanzania, Mauritius and Kenyan stock indices. There is also a unidirectional shock or news transmission from oil to Nigeria, Tanzania, Kenya, and Ghanaian indices. This is not surprising for Nigeria, as the oil price movements have a significant impact on the Nigerian economy. There is evidence suggesting bidirectional volatility between oil returns and world, South Africa and Tunisian stock indices; and there is evidence of bidirectional shocks or news transmission between oil volatility and Morocco, Tunisia and the world stock indices.

CHAPTER 5

5.1 Discussion, conclusion and future recommended studies

5.1.1 Discussion

It is evident that empirical findings from literature does support the relationship between oil price volatility, stocks and other economic variables like GDP, exchange rate, interest, unemployment and inflation (Adeniyi et al., 2011; Chen, Liu, Wang & Zhu, 2016; Zhang *et al.*, 2008; Basher, Haug & Sadorsky, 2012), and the stock market can be a good indicator or barometer for economic performance. Basher et al. (2012) also support the argument as they indicated that high stock prices in emerging markets signal the expectations of higher economic growth in the future. The financial crises of 2008, coupled with the Arab Spring uprising, the Greek crises which largely impacted the Eurozone with potential spillover towards the global markets and also local economic factors may have contributed to oil prices movements and volatilities.

Brent crude will remain a critical commodity for African emerging and frontier markets. As Brent crude is an important component for production of goods, it may drive economic variables like exchange rates, inflation and interest rates. High oil prices will affect the stock returns through the discount rate or high input costs when producing goods. The results may be a reduction of economic profits, which will ultimately reduce dividends and share prices. The ripple effects may spread to the economic variables like unemployment as firms may reduce staff to cut costs; inflation as high input costs may be followed by high prices of goods resulting in higher inflation. High inflation may trigger the monetary policy makers to adjust to higher interest rates, as one of the tools to curb inflation. This is an indication of how oil price movements can be important for policy makers as it may give an indication of future economic prospects. In 2016, both the Nigerian and South African economies were facing sluggish economic growth. The Nigerian economy is heavily dependent on oil, so oil price movements will continue to have a significant impact on its economy.

Low oil prices in 2015 have put adverse pressure on the Nigerian government's fiscal policy, with the ripple effect of putting the economy into a recession in 2016. South Africa may also feel the impact of the oil price movement through the volatile exchange rate, inflation hovering above the Reserve Banks' target of 6%, standing at 6.6% as of December 2016 (SA Reserve Bank, 2017). These sentiments are similar to other African markets, with the Namibian dollar currently pegged to the South Africa Rand, and South

Africa being one of Botswana's large trading partners. According to the IMF (2016) report, the Kenyan economy is feeling pressure driven by the external volatilities in global markets including oil markets, which is driving high inflation.

As discussed, these factors are putting pressure on governments' fiscal policies, resulting in potential tax hikes, increase in external borrowing and possible unfavourable ratings from the rating agencies. Unfavourable ratings will affect foreign direct investments (FDI) as low ratings indicate high risks for investors. According to the IMF (2016) report, Moroccan Reserve Bank governor, Mr Mohammed Boussaid, concedes that the low oil prices and persistent conflicts continue to have marked effects on economies in the Arab states, including Egypt and Tunisia. This is because revenues have decreased, hence impacting the fiscal, and potentially the stock prices. The above discussion does indicate that oil prices and volatilities may be an indicator for investors to take a position based on the oil price movements in the medium to long-term. The reason for doing this is to maximise economic profits on fixed income, equity investments or any other alternate investments like real estate, commodities, hedge funds, and private equity.

5.1.2 Conclusion

The results suggest that there is significant and compelling evidence confirming relationship between the oil price shocks, oil price volatilities and African emerging and frontier markets. This is in the form of oil price shocks and volatilities being unidirectional to most emerging and frontier markets. The results are consistent using both the ARDL and Bivariate BEKK GARCH models. The study's objectives of examining the behaviour of stock markets across time and analysis of relationship between stock market and oil price volatilities within the chosen African markets have been achieved.

5.1.2 Future recommended studies

To expand further on this study, it would be interesting to find the significance of economic variables (if any) like unemployment, interest rate, inflation, GDP and exchange rate towards the African stock markets in relation to oil volatility and price shocks. Future studies can include all oil producing/exporting countries like Angola, Algeria and Libya, in the African market context, in order to investigate any potential markets co-movements with their respective neighbour countries. It will also be of great benefit to examine long-term monthly data or a more frequent data in a weekly or daily basis. Furthermore, a research based on oil price shocks and volatility per stock sector might be invaluable to literature from an African market perspective, instead of using the overall index. Such a research will give an indication to investors on which stocks react most to oil volatility and price shocks.

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