

https://dspace.org/

Stock market effects of the 2015 presidential election in Tanzania

Masima, Nyangwe Job

2021
https://hdl.handle.net/10539/32641

Downloaded from a DSpace repository. https://dspace.org/



MASTERS OF MANAGEMENT IN FINANCE AND INVESTMENT

A RESEARCH REPORT ON

Stock Market Effects of the 2015 Presidential Election in Tanzania

Submitted to

Wits business School

University of the Witwatersrand

Johannesburg, South Africa

Submitted by:

Nyangwe Job Masima (1933572)

January 2021

Supervisor:

Professor. Odongo Kodongo

ABSTRACT

In this study we analyse for the first time the impact of the 2015 presidential elections on the returns of the Dar Es Salaam Stock Market. A wide range of studies have been conducted on the impact of presidential elections on stock market returns of many countries. Most of these studies have been piloted in developed nations, very little in Africa and no known study in Tanzania. This study provides new knowledge on these fronts for the finance literature in Africa, developing markets and Tanzania.

The study was based on event study methodology and employed the market model to estimate the expected return, consequently leading to the computation of abnormal returns. The event days were the 12th July 2015 (nomination day) and 29th October 2015 (election day). Furthermore, a robustness of event study was conducted by testing for structural breaks to determine exogenous dates to confirm event dates assumed at the beginning of the study. A variety of GARCH models were further used to test for the effect of the presidential elections on the returns of the DSE.

The graphic representation of the Dar Es Salaam stock market from the period 4th January 2010 to 30th December 2019 indicated an increase in volatility clustering over time compared to period before 2014; highly volatile markets lower investor confidence. Different patterns of abnormal returns were observed for both nomination and election period. The NP10 test indicated negative averages during the break and post break period while positive returns were observed during the pre break period. It is not unusual for this to happen during a period of structural break, but that it continues after, implies that the market is still reeling of the uncertainties generated by the Presidential election activities. The empirical findings showed that the 2015 presidential elections had an impact and sticky effect on the returns of the Dar Es Salaam Stock Market. The study recommends that investors investing on the Dar Es Salaam stock market should carefully plan and carry out investments desicisions during and after the period of general elections as returns could be affected either positively or negatively during this period

DEDICATION

This work is dedicated to my daughter, Manka Azania Masima Ajusi. My The Lord God give you the gift of knowledge and the desire to learn

ACKNOWLEDGEMENT

First and foremost, I would like to praise and thank God, the Almighty, who has been the source of my strength and has granted me with countless blessings and knowledge to be able to finally accomplish my research.

To my supervisor, Professor Odongo Kodongo, I would like to express my deepest appreciation for your patience, guidance, encouragement and constructive criticism of this research. Your positive outlook and confidence in my research inspired me and gave me confidence.

To my husband and love of my life, Victor Draga Ajusi, who has given me extra strength and motivation to get things done. Thank you for always believing in me even when I had lost belief in myself. To my adorable daughter, Manka Azania Masima Ajusi, who joined us when I was writing my thesis. Thank you for giving me unlimited happiness and pleasure.

My deepest gratitude goes to my parents, H.E. Ambassodor Job Daudi Masima and Mrs Yohanna Masima, without whom I would never have enjoyed so many opportunities. I thank you both for laying a solid foundation in my life, for your limitless love, support and encouragement.

My unquantifiable thanks goes to my parents- in-law, Dr John Ajusi and Dr Stella Ajusi. Thank you for your prayers, support and encouragement to finish my thesis. I could not have wished for a better second family.

I would like to express gratitude to all my sisters, Elizabeth Masima, Muyalaza Masima, Mwendeche Masima, Brenda Ajusi, Zanele Ajusi and Slyvia Sithole. You all played a big role in finishing my thesis. Thank you for all the encouragement and support.

To my classmates, thank you for making this journey enjoyable. A special thanks to Peterson Owusu Jnr for his guidance, support and reassurance during the course of this research.

Finally, but definitely not least to my beautiful country, Tanzania, the inspiration for my research thesis. I am so grateful and proud to be a child of your soil. May The Lord Almighty continue to bless and guide this great nation.

DECLARATION

I, Nyangwe Masima, with student Number: 1933572, declare that this research report is my own work except where indicated in references and acknowledgments. It is submitted in partial fulfillment 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……

Nyangwe Job Masima

Contents

Effects of Tanzania's 2015 presidential election on stock market returns 1
Chapter One 9
1.1. Introduction 9
1.2. Research Problem 10
1.3. Elections in Tanzania 12
1.4. 2015 Presidential Election 13
1.6. Dar Es Salaam Stock Exchange 14
Chapter Two 17
2.1. Literature Review 17
2.2. Theoretical Literature 17
2.3. Empirical Literature 19
Chapter Three: Research Methodology 22
3.1 Introduction 22
3.2 Data and sample period 22
3.3 Statistical methodologies 23
Chapter Four: Results and Discussion 29
4.1 Introduction 29
4.2 Preliminary analysis 29
4.4 Robustness test: structural breaks 33
4.5 Volatility modelling: GARCH models 34
Chapter Five: Conclusion and recommendation for further studies 44
5.1 Conclusion 44
5.2. Recommendation for further studies 45

List of Figures

Figure 1: Price and return series chart of Tanzania stock market index.....15
Figure 2a: Abnormal returns for pre-nominations and post--nominations in Tanzania stock market index.....30
Figure 2b: Abnormal returns for pre-nominations and post--nominations in Tanzania stock market index.....30
Figure 3: Conditional variance plots of the DSEI samples. Note: (a) - (EGARCH(1,1) for full sample period, (b) - sGARCH(1,1) for pre-break period, (c) - sGARCH(1,1) for break period, & (d) - EGARC(1,1))for post-break period. 41
Figure 4: News impact curves for DSEI samples. Note: (a) - (EGARCH(1,1) for full sample period, (b) - sGARCH(1,1) for pre-break period, (c) - sGARCH(1,1) for break period, & (d) - EGARC(1,1))for post-break period. 43

List of Tables

Table 1: Test of significance for abnormal returns 29
Table 2: Summary statistics 31
Table 3: Stationarity tests 32
Table 4: NP10 unit root test structural breaks test 33
Table 5: Results of volatility models of the Tanzania stock market index for the full sample period..35
Table 6: Results of volatility models of the Tanzania stock market index for the pre-break sample period.....36
Table 7: Results of volatility models of the Tanzania stock market index for the break sample period 37
Table 8: Results of volatility models of the Tanzania stock market index for the post-break sample period.....38

List of Abbreviations

AIC	- Akaike Information Criterion
BIC	- Bayesian Information Criterion
CCM	- Chama Cha Mapenduzi
CMSA	- Capital Market and Security Authority
DSE	- Dar Es Salaam Stock Market
DSEI	Dar Es Salaam Stock Index
EGARCH	-Exponential GARCH
EMH	- Efficient Market Hypothesis
GARCH	- Generalised Autoregressive Conditional Heteroscedasticity
GJR-GARCH	- Glosten Jagannathan and Runkle
HQIC	- Hannan-Quinn information criterion
NP(2020)	- Narayan and Popp (2010)
SGARCH	-Standard GARCH

Chapter One

1.1. Introduction

The research conducted in this paper studies the effect of political events (triggered by the 2015 presidential elections in Tanzania) on returns of the Dar Es Salaam stock market. There are many factors influencing the operations and performance of a country's financial markets; change in composition of investors, availability of other investment assets and market sentiment are all contributing factors (Mendelson and Robbins, 1976). How stock markets are influenced by various factors are of interest to investors researchers and government because they play an important role in an economy.

A government usually attempts to direct its economy. Policy changes normally result from the formation of a new government. Macroeconomic effects, like inflation, unemployment and economic growth, are a result of policy choices by the government (Dangol, 2006) .Thus, the economic outcomes of a country are not exclusively the consequences of the economy alone but are similarly reliant on the policy choices of the government (Dangol, 2006). Economic policies enacted by different political parties have the potential to shift the economy in a different direction, this is then observed in the returns to shareholders (Li and Born, 2006).

Political risk is defined as a change in value that arise as a consequence of political action (Ross, Westerfield, and Jordan, 2008). Some countries have more political risk than others. The extra political risk may lead to firms requiring a greater return on investment to reimburse the risk of higher unstable political environment. Pástor and Veronesi (2013) identified that political uncertainty demands a larger risk premium in a weaker economic environment. The study further states that political risks make stock more correlated and more volatile, especially in a weak economy. The study of Political risk and stability of stock markets are of great importance to market's regulators and investors (Chau, Deesomsak, and Wang, 2014). The political environment during general elections impacts the performance of the financial market (Kabiru, Ochieng, and Kinyua 2015). Previous researchers like Campello (2009) and) Bialkowski, Gottschalk, and Wisniewski (2008) concluded that the political uncertainty surrounding elections results in economic uncertanity, increasesing investors risk aversion.

Stock markets play an important role in the operation of a country as they influence the general performance of a country and government activities. Previous studies like Chau et al., (2014); Kim and Mei, (2001) have indicated a close relationship between political risk and stock markets. Stock markets can also be affected by a shift in fiscal and monetary policies normally associated with a change in government.

The first general election in Tanzania was held on the 29th of October 1995. Five general elections have been held in the United Republic of Tanzania of which Chama Cha Mapinduzi (CCM) has always retained control. Tanzania has built a reputation for long standing peace and stability, during presidential elections, in contrast to its Central and East African neighbours (Anyimadu, 2016). Due to the popularity of the rulling party CCM, the general elections in Tanzania have been predictable, allowing CCM to seize more than 60% of the votes since 1995 (Hasan 2004). However, the 2015 genral election had some unusual features compared to the previous four general elections:

1. For the first time in the history of presidential elections in Tanzania, the support for CCM during the 2015 election fell below 60%.
2. The selection of a presidential candidate for the rulling CCM in July 2015, exposed fractures in the party that had never been witnessed since independence in 1961 (Anyimadu 2016).
3. The results of the 2015 elections were less predictable than those of previous polls, indicating popular demand for change from the political status quo.This election was regarded as the most fierce the governing party faced since 1995 (Bamwenda 2018).

Due to the unpredictability element of the 2015 presidential election in Tanzania, it is possible to study the relationship between political uncertainty surrounding the elections in 2015 and the returns of the Dar Es Salaam stock market.

1.2. Research Problem

The Dar Es Salaam Stock Exchange (DSE) was established in 1998 and it is one of the youngest stock exchanges in Africa. Capital markets in Africa are increasingly becoming important as more people are now diversifying their portfolios from developed markets to emerging markets due to the reasoning that these markets offer a higher return than those in advanced markets. Thus investors in developed markets are forced to look beyond their boarders (Korkpoe and Owusu Junior, 2018).

There has been little empirical studies in Africa on the effect of political activities (such as presidential elections) on the returns of stock market (Aliyu, 2019; Kabiru, Ochieng, and Kinyua, 2015). Majority of such studies have been conducted in developed markets (Beaulieu, Cosset, and Essaddam, 2005; Füss and Bechtel, 2008; Niederhoffe, Gibbs, and Bullock, 1970). In accordance with Nguthi (2013), the effect of news surrounding political events on stock exchange has been an increase in the volatity of prices. Mixed results were obtained by Soultanaeva (2008) who studied the impact of political news in Baltic stock markets. Some markets showed increased political risk, others showed decreased risk and some seemed unaffected. This led to the conclusion that different markets react differently to political news. Considering this conclusion, investors in developing markets cannot rely on studies done in developed stock markets since they operate in environments different to those found in developed countries. Investors find it difficult to make investment decisions during the times of political events due to the uncertainty surrounding such events. As opposed to other elections held in Tanzania, the 2015 elections were unique as they were more unpredictable. The literature review further shows that no know studies of this nature have been conducted in Tanzania on the DSE. Due to the shortage of practical studies on the "effect of presidential elections on stock market returns", individuals and institutions do not have scientific knowledge to assist them to make decisions on equity investments during these times in Tanzania.This study provides new knowledge on these fronts for the finance literature in Africa, developing markets and Tanzania.

From a methodological point of view, this study transforms and lengthens on the approach used in previous studies. It is important to note that majority of the studies on this topic use an event study methodology only (Dangol, 2006; Kabiru et al., 2015; Obradović and Tomić, 2017), whereas in this paper a robustness of event study is conducted by testing for structural breaks to determine exogenous dates to confirm event dates assumed at the beginning of the study. A variety of GARCH models have been used in this paper to test for the effect of the presidential elections on the returns of the DSE. We have chosen to model volatility using the AR (1)-GARCH (1,1) for the standard, exponential and GJR in order to capture the persistence, asymmetry, and the impact of news in the stock return. Other prior studies Beaulieu et al. (2005); Chau et al. (2014) have used GARCH based analytic framework to measure stock volatility without examining persistence. While investors aim for high returns, they come at the cost of high risk. Therefore, superior knowledge on the patterns of risk (as indicated by

volatility) and how to model them is very important. It aids in effective decision making on the asset in question

The results of our analyses will be beneficial to investors interested in investing in African markets as well as policy makers and financial authorities wishing to asses the role in which political actions and events could trigger stock market movements. Many researchers have looked at the relationship between stock market performances and political cycle (Dangol, 2006; Niederhoffe et al., 1970). However, majority of the studies do not cover the African continent. The main variable will be the Dar Es Salaam stock index.

1.2.1. Research Objective

The objective of this study is to find out whether the 2015 presidential elections had any effect on the Dar Es Salaam Stock Market.

1.2.2. Research Question

The study pursues to answer the following questions:

1. What was the reaction of the stock returns at the DSE during the October 2015 elections?
2. Did the 2015 presidential elections affect the volatility and stock market returns of the DSE?

1.3. Elections in Tanzania

Tanganyika obtained its independence in 1963 shortly after which former president Julius Nyerere and the Tanganyika African Nation party banned opposition political parties. In April 1964, straight after the amalgamation of the previous state Tanganyika and Zanzibar, the United Republic of Tanzania was born. Later, Tanzania was amongst the first countries to welcome the multiparty political system of governance in Africa, in 1992. The first multi – party presidential and National assembly elections were held in October 1995.

Presidential elections in Tanzania have all been decided in a one-round, allowing plurality competition and takes place every 5 years.

Since the introduction of the multi-party system, Tanzania has held 5 general elections in which Chama Cha Mapinduzi (CCM) retained control position in all the elections. The first general election was held on the 29th October 1995 and the second general election was held on 29th October 2000. Candidate Benjamin Mkapa from CCM won both of these presidential elections. The third general elections were held on the 14 December 2005 and the fourth held on the 31st

October 2010. These presidential elections were won by candidate Jakaya Kikwete. The fifth general elections were held on the 29th October 2015.

1.4. 2015 Presidential Election

On the 12 of July 2015, Chama Cha Mapinduzi (CCM) elected John Pombe Magufuli as their presidential candidate, beating the Justice Minister Asha Rose Migiro and UN deputy secretary Amina Salum Ali. This turn of events was seen as "surprising" as Magufuli had not been initially seen as a frontrunner but was amongst the shortlisted from the list of 40 other candidates that included the former Prime Minister, Edward Lowassa. Although Magufuli had been a long serving Minister since being elected to parliament in 1995, he had never held a leadership position within the party. The selection of John Pombe Magufuli by the party as its presidential candidate was unexpected (Eriksen, 2018). Dr Magufuli was never part of the inner circles of those governing CMM thus his cadency for presidency came as a surprise (Bamwenda, 2018)

After losing Chama Cha Mapinduzi's nomination, in an unprecedented move, Edward Lowasa moved to the country's main opposition party, Chama Cha Demokrasia with several high raking followers. He became the most senior ruling party official to ever move to the country's opposition. This move created disquiet in the political environment in the country. The intra party hierarchies in the ruling and opposition parties were shaken and elections results were unpredictable.

Another significant event that took place was that for the first time in the history of Tanzania politics, leading opposition parties came together to share resources. This move strengthen the opposition parties' status and gave them a strong positioning that has never been seen before in Tanzania (Bamwenda, 2018)

Long lines of queuing voters, that has never been seen before since independence in 1961, were observed (Bamwenda, 2018). Edward Lowasa attracted more attention on the campaign trail than Magufuli himself; during his move to the opposition party he was able to convince a number of high profile politicians from the ruling party, CCM, to also move to the main opposition, accusing CCM of corruption. On the other hand, opinion polls were contradictory with some favoring the CCM candidate, Magufuli, while others favored the opposition candidate, Lowasa. The IPSOS/Synovate poll had Magufuli leading with 62% and the Twaweza polls also had Magufuli leading with 66% ahead of Lowassa (Chande, 2015). However, three opinion polls conducted under Ukakwa Coalition wing by local and foreign

pollsters showed Lowassa winning by 74%, 76%, and 79% at different points in time (Lyimo, 2015). For the first time CCM had an equal contender.

The presidential election in Tanzania is based on popular votes, the winning candidate has to hold more than 51% of citizens votes. The 2015 elections were concluded on 29 October 2015 where, to a lot of people's surprise, John Pombe Magufuli was announced the winner, ahead of Edward Lowasa from the opposing party, with 58% of the vote.

The 2015 presidential elections results were historic. For the first time in the history of presidential elections in Tanzania, the support for CCM during the 2015 elections fell below 60%. In the four previous elections, the CCM's lowest share of the vote was in 2010 with over 62% and its highest in 2005 with over 80%.

There has been a lot of speculation regarding how the 2015 presidential elections have affected the Dar Es Salaam Stock Exchange market but no empirical study has been conducted to analyse the relation. This study aims to cover this gap.

1.6. Dar Es Salaam Stock Exchange

Stock market plays a vital role in the economy of a country. According to Zuravicky (2005), many economists have looked at obtaining an explanation for the fluctuating stock prices. The stock prices are influenced by multiple factors, some of which tend to be more complex and volatile than others.

The Capital Market and Security Authority (CMSA) established the Dar Es Salaam stock exchange (DSE) under the Capital Market and Securities Act of 1999 (DSE, 2014). On the 15th of April 1998 the DSE started trading. Tanzania Oxygen Limited (TOL) was the first listed security on the exchange. Five years later, the exchange had expanded to another 5 listings one being, Tanzania Tea Packers Limited (TATEPA) a purely private sector company while the others were former parastatals which were driven by the Government's privatization exercise. During the subsequent years, other formerly private companies listed on the DSE as part of their corporate growth strategy to raise capital.

The DSE operates from Monday to Friday. The company provides various services such as risk management, clearing and market data services. Companies listed on the Exchange use its platform to raise capital by issuing equity and debt securities to investors. As of 31st December 2019, there were 27 companies listed at the DSE with a total market capitalization of TZS 17

Trillion (DSE, 2019). Major industries accounted for on the exchange are banking and finance, insurance, aviation and local food beverage productions.

The Capital Market and Security Authority regulates the operations of the capital market in Tanzania. The sale of securities abroad has to be approved by the CMSA. Before the 2014 amendment foreign ownership was limited to 60% of the total value of the listed companies. This restriction was lifted in 2014 allowing no limits on foreign investment. According to the CMSA 90.1% of the buy side activity were done by foreign investors in the financial year 2015/2016.

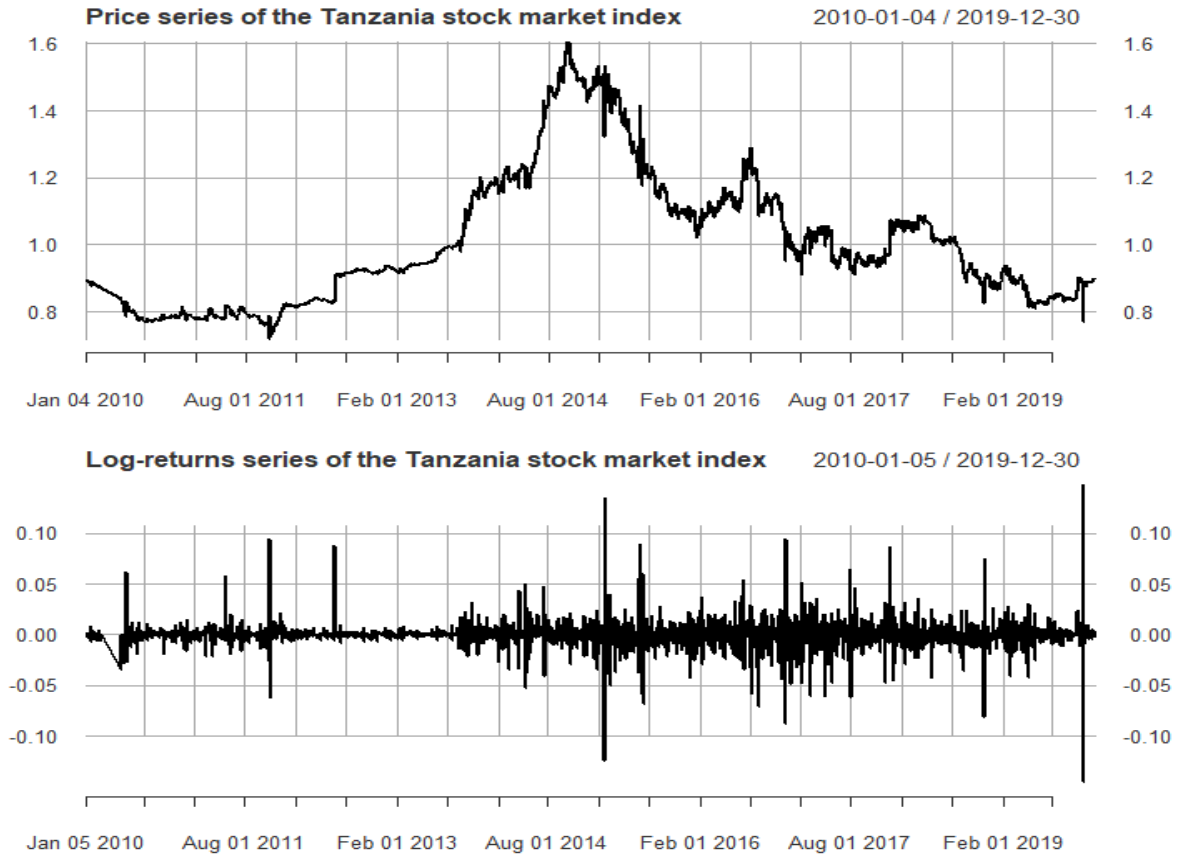


Figure 1: Price and return series chart of Tanzania stock market index

From Figure 1 it is clear that the 2015 presidential elections could have had an impact on the Tanzania stock market as shown in the price pattern of the index. While there was rising trend from early 2012, this trend seemed to have increased from early 2014 and peaked prior to the start of the presidential elections race in the middle of 2015. Given the combination of both good and bad news (i.e. uncertainty) as a result of campaign and manifestos, there is heightened volatility in the index at the historical heights. But there is a downward trend from late 2015, when the elections were finally held, and when the winner was announced. The index also

seems to revert back to its trend five years' prior for the next five years ending in December 2019. However, this latter downward trend shows larger jumps in the price.

Following the dynamics observed in the stock market index, it is possible to investigate structural breaks that may have occurred due to the presidential election. Further, we can model the uncertain and unpredictable price movements in the stock index amidst the turmoil of the presidential elections in the country.

The rest of the paper is as follows: chapter two reviews the literature on the topic of this paper, chapter three shows the methodology used, chapter four presents the results and chapter five concludes the study.

Chapter Two

2.1.Literature Review

A number of theories and academic arguments have been published to explain the relationship between stock market performance and political information. This chapter reviews some theoretical, as well as empirical, issues that form the groundwork for the study.

2.2.Theoretical Literature

The Efficient Market Hypothesis (EMH), introduced by Fama (1970) assumes all relevant information are reflected in the share price. Therefore, all public information should be incorporated in the financial markets. This theory implies that; no amount of analysis can give an investor an upper hand over another. The random walk hypothesis states that stock market prices evolve randomly thus there is no way to make a prediction based on past values of the time series.

Fama, (1970) further identified tree forms of efficiency describing the level of which information is assimilated in the stock prices. The first form is known as the week form efficiency; this is when only historical information is reflected on stock prices. The second form identified is the semi strong form of efficiency where public data well-known to all market applicant is reflected on the stock values. Lastly, when all public and private data known to any market applicant is imitated on stock prices, this level is known as strong market efficiency.

In an efficient market significant new public information should reflect immediately. An efficient market can be defined as, a market where there's an outsized number of reasonable and sensible investors vigorously competing with each other trying to predict future market prices. Competition amongst these observers result in the past, the current and the future information reflected in market values.

An alternative hypothesis is the inefficient market, explored by Hadi (2006), indicating that stock prices are not accurately reflecting the new information. There are various reason as to why stock prices might not accurately reflect new information: 1) the investor might not be able to construe the new information correctly, 2) access to new information might not be available to investors, 3) high transaction costs in trading might be an hindrance etc.

While studies such as Alagidede, Panagiotidis, and Zhang (2011); Ntim et al. (2011); and Appiah-Kusi & Menyah (2003) have discovered suggestion of inefficiencies in of African equity markets bordering on predictability of both returns and volatility, there are equal

evidence to the fact that the stylised facts are conditionally varying (Piesse & Hearn, 2002; Tooma, 2003; Algidede & Panagiotidis, 2006).

A few empirical studies have been conducted on weak form efficiency on the Dar Es Salam Stock Market that provide conflicting evidence. The study conduct by Katabi and Raphael (2018) on the efficiency of the Dar Es Salaam stock Market indicated that the returns series did not act randomly, thus it was resolved that the DSE is not a weak form efficient market. Inefficacy of the stock market suggests that analysis can give an investor an upper hand. The results obtained by Guney and Komba (2016) suggested that a random walk was identified on the return series based on price indices but when a similar test was performed for the returns based on return indices, it was noted that that those series were not a week form efficient. Mixed results were also obtained in Njuguna (2016); while the runs test and the unit root test did not support the EMH, the robust variance test did.

Behavioral finance theory explains how reasoning error influence financial decision. The foundation of behavioral finance is that orthodox financial theory does not take real people into account (Barberis and Thaler, 2003). Behavioural finances argues that not all investors are rational and sensible as presumed by conventional theories. The study further classifies the irrationalities in two broad categories: firstly that the information obtained by investors is not always processed correctly resulting in an unfitting probability distribution about future rates of returns; and secondly even given a probability distribution of return, investors can still make inconsistent or systematic suboptimal decisions. Kahneman and Tversky (1973), indicated that people lean towards developing forecasts that are too ambitious this is attributed to the reasoning that too much emphasis is given to recent experience compared to prior beliefs when making forecasts.

Behavioral finance highlights the fact that, emotional factors play an important role in influencing financial markets. This theory infers that markets may be inefficient because of emotional errors attributed to certain classes of investors. Those who follow the arbitrage model in an efficient market are thus expected to recognize and exploit these biases when they exist till stock values are restored to market equilibrium.

Campbell et al. (1998), for instance, indicate that bad news has more sway on the stock market and they are portrayed by more extreme spikes in volatility than good news in the market. It is not unusual for stock markets to experience boom and bust cycles, especially with the expectation of different form of news which play on the sentiments of investors. Stoval (1992)

highlighted that a lack of information amongst market participants creates a situation where the buying and selling of shares is done on impulse rather knowledge resulting in returns being low and further depressing the penetration of the stock market to the mass market.

2.3.Empirical Literature

Obradović and Tomić (2017) investigated in the USA how the event of a presidential election held on the 6th of November 2012 affected stock returns on the New York Stock Exchange. 85 Companies on the stock exchange were analyzed and the main finding was that the event of the presidential election affected the return movement of the selected stocks. The study further noted that a sufficient number of tests confirmed the effect had statistical significance.

Niederhoffe et al. (1970) analyzed the long period effect of the market response to the outcomes of the presidential election in the United Republic of America. They determined that the market reaction differs depending on the winning candidate's party. It was further discovered that, after the triumph of the Republican contender there was a growth in the market but a fall was observed after the victory of the Democratic candidate.

Valadez (2012) looked at the connection between the US political parties in presidential office and the S&P 500 performance, volatility and risk. The purpose of the study was to make an observation on whether or not there were any connection between the political party holding office and historic market performance. They found that there was no substantial variance between the political party and S&P 500 performance.

Füss and Bechtel (2008) were the first to investigate the effect of expected government partisanship, in the 2002 German federal elections, on stock market performance. Their results indicated that small firm stocks returns were allied positively to the likelihood of a right leaning coalition winning and negatively allied to the likelihood of left leaning coalition winning the election. Furthermore, the observations showed that there was increase in volatility as the electoral prospects of right-leaning parties improved, while increased electoral uncertainty reduced volatility effects.

Bialkowski, Gottschalk, and Wisniewski (2008) analysed to see if national elections caused high market volatility in 27 OECD countries. The study found that during the week neighboring the elections, the rise in volatility reaches a double level.

Kim and Mei (2001) looked at Hong Kong and investigated the market effect of political risk. The observed results revealed that there was a substantial impact on market volatility and

returns due to political progress in Hong Kong. Based on presidential elections held between 1999 and 2019, Aliyu (2019) investigated whether presidential elections affected stock market returns in Nigeria. Findings showed that when the PDP government was in office bearish stock market returns were observed during presidential elections, whereas when the APC was in office bullish market returns were observed during elections. Furthermore, positive impact on stock market returns were only observed during the 2011 election.

Kabiru et al. (2015) investigated the relationship of presidential elections on stock returns at the Nairobi security market. The study adopted an event study methodology and analysed the general elections held in 1997, 2002, 2007 and 2013. The study showed that in 2002 and 2013 general elections the cumulative abnormal returns were insignificant, while during the 1997 and 2007 elections cumulative abnormal returns were identified to be significant at a 5% level of significance. The study also noted that the market reaction, whether positive or negative, was dependent on the volatility of the election atmosphere.

Menge (2013); Nguthi (2013); Zainabu (2014) also examined the consequence of presidential elections on stock market returns at the Nairobi security market using an event study. The results were consistent and showed that Nairobi Stock Exchange significantly responds to political events. Chau et al. (2014) studied the influence of political uncertainty (caused by civil uprising in the Arab world) on volatility of stock markets in the MENA area by using a GARCH based analytical framework. In general, they found that political uncertainty contributes to the volatility of the financial markets. Substantial escalation in the volatility of Islamic indices throughout the era of political unrest was observed.

Dangol (2006) looked at the effect of unanticipated Political Events on stock returns in the Nepalese stock market using the event study analysis and found that good news political announcement resulted in positive abnormal returns while bad news political announcement caused negative abnormal returns. The paper also found that, there was a sturdy link between political uncertainty and stock returns.

Wanjiru (2000) determined the effect of both fiscal and monetary policy actions on stock market performance in Kenya. The short run results showed that both anticipated and unanticipated components of monetary and fiscal policies pronouncement and changes affected the performance of the Nairobi Stock Exchange (NSE). The Long run results indicated that anticipated monetary policy actions, together with unanticipated fiscal policy adjustment,

affected the stock market performance negatively. The unanticipated policy action and the anticipated fiscal policy actions do not affect the stock market performance.

Another study in the African context was conducted in South Africa by Brooks, Davidson, and Faff (1997). The study examined the effect of political change that took place on February 2nd 1990 on the Johannesburg Stock Exchange; the findings indicated that market volatility is closely allied to political instability.

Extensive studies have been conducted in various stock markets examining the impact of political events and stock markets. Results from various studies have indicated that there is a relationship between political events and the stock markets. Most of these studies have been conducted in developed countries, very little in developing countries and no known studies have been conducted in Tanzania. To contribute to filling this gap in the African context, this study empirically examines the effect of the 2015 presidential election to the Dar Es Salaam Stock Market. Furthermore, the foregoing review shows that different studies applied different methodologies across a number of countries, to study the impact of political events to stock market returns. Majority of the studies, especially those conducted in Africa, use the event study methodology and very few use GARCH based analytic framework to measure stock volatility of political events on stock market returns.

This study offers insight into the risk behavior in the stock market and how to strategies for both local and international investors. Furthermore, this analysis creates a deeper understanding into how election euphoria can affect the whole financial system of an economy. Hence, policy makers will have the tools to deal with such situations more appropriately in order to safeguard the financial system as well as attract international equity investors to Tanzania. This is important because international investors are always considering diversifying into emerging and frontier markets as they have the promise of higher returns than advanced markets. The findings of our analyses will be beneficial to government and policy creators as it will direct the formulation of policy regarding management of security exchange during elections to ensure market stability.

Chapter Three: Research Methodology

3.1 Introduction

This study employs a purely quantitative approach with secondary data to achieve the objectives. All the techniques are systematically selected in order to provide a coherent assessment of whether the Presidential elections had any substantial effect on the stock market of Tanzania or otherwise. We use different techniques which converge to form an event study. An event study examines return behavior for a sample of firms experiencing a common type of event which might take place at different points in calendar time or might be clustered at a particular date (for example a regulatory event affecting an industry). Given the unavailability of the individual stock data, we use the single main stock market index on the Dar Es Salam Stock Exchange (DSE) index as the proxy for the stock market. As in index is capture the dynamics in the financial sector.

For the effect of Presidential elections on the stock market, we perform trend analysis and examine a battery of statistical properties before and after the fact on the stock market index.

3.2 Data and sample period

The study is conducted around two events. The first date is the day of the presidential candidate announcement by political parties (12th July, 2015). The second date is chosen as 29th October 2015, the day that John Pombe Magufuli was announced President elect of Tanzania. For these reasons, we analyse the effect of Presidential election on the stock market following this pattern: pre-election period (4th January, 2010 to 11th July, 2015), election period (12th July, 2015 to 29th October, 2015), and post-election period (30th October, 2015 to 30th December, 2019). We have chosen the end date in order to avoid the impact of the Covid-19 pandemic on the stock market. The start date also does not coincide with any significant event in Tanzania or the global market to alter the dynamics of the stock market. In addition, the start and end dates approximately balance which is good for this analysis. This requires a different study which falls beyond the scope this thesis. The selection of periods is also inspired by Campbell, Lo, and MacKinlay (2019);Campbell et al. (2019) and Kothari and Warner (2007). Daily closing price frequency of the stock market data in US dollars is used. This was extracted from the Bloomberg Terminal.

3.3 Statistical methodologies

3.3.1 Abnormal returns from electioneering activities

To set the stage for the volatility models spanning the nominations and election periods, we follow the event study approach to determine abnormal returns emanating from these periods. Event study techniques have been widely used to test the effects of economic, political, or social events on stock prices (Basdas and Oran, 2014). One of the most preferred models in the many alternatives for implementing event study is the market model (see Kamakura, 1995; Cheung, 2011; Curran and Moran, 2007).

The market model can be represented as

$$R_{it} = \beta_0 + \beta_1 R_{mt} + \varepsilon_t, \qquad (3.1)$$

where R_{it}, R_{mt}, and ε_t are daily returns of Tanzanian stock market index, are daily returns of market portfolio index, and error term, respectively. For an African equity portfolio index, we have selected the Morgan Stanley Capital International (MSCI) Emerging Frontier Markets Africa Index. It has 69 constituents and covers approximately 85% of the free float adjusted market capitalisation in each country[1]. In order to obtain abnormal returns for the stock market index, we calculate the expected return, $E(R_{it})$ for the security from the market model (Serra, 2002). Abnormal returns, AR_{it} are calculated as

$$AR_{it} = R_{it} - E(R_{it}). \qquad (3.2)$$

Given that there is only one security (the Tanzanian stock market index) in this study, we are unable to estimate average abnormal returns (AAR) and cumulative average abnormal returns (CAAR). Lastly, we choose the event window of five days before and five days (including the event day) after both the nominations and election dates (i.e. (-5…+5)). It is obvious that abnormal returns will always appear. What is important that we test its statistical significance between the original returns of the stock returns using. We use the two sample t-test for this purpose. We test the hypothesis

$$H_0: R_{it} = AR_{it}, H_1: R_{it} \neq AR_{it} \qquad (3.3)$$

Note that returns are calculated as $\ln(1 + R_t) = \ln(P_t) - \ln(P_{t-1})$, where P_{t-1} and P_t are the previous and current prices, respectively. It is the continuously compounded return (natural

[1] https://www.msci.com

logarithm of the simple gross return of an asset). Tsay (2005) notes that the statistical properties of log-returns are more tractable.

3.3.2 Structural breaks and robustness

Given that there are significant abnormal returns for the event windows in series as seen in 3.3.1, this can suggest structural breaks in the time series, hence the breaks points are endogenously chosen based on the election periods. However, high frequency data usually exhibit structural breaks. In order to perform further statistical analysis on the sub-samples, we find a robust exogenously determined structural breaks to see if they coincide with the predetermined sub-sample periods. We employ the Narayan and Popp (2010) unit root model to account for the existence of structural breaks in the Tanzania stock market index. This is an important contribution to the literature on event studies since many have only relied on the event dates for analysis. This approach has been used in studies such as Narayan, Liu, and Westerlund (2016); Narayan and Sharma (2015); Westerlund and Narayan (2013). The latter accounts for structural breaks as well as heteroscedasticity. Nonetheless, Narayan and Popp (2013) show that Narayan and Popp (2010) is significantly superior to Westerlund and Narayan (2013). That is why Narayan and Popp (2010) is chosen for this study.

The Narayan and Popp (2010) (NP10) structural break test is based on the augmented Dickey–Fuller-type (ADF) and Kwiatkowski-Phillips-Schmidt-Shinn (KPSS) test for unit roots and accounts for two structural breaks. The two breaks are as follows: M1 allows for two breaks in the intercept and M2 allows for two breaks in both the intercept and trend of the series. For the deterministic component of the ADF, $y_t = d_t + \mu_t$ with μ_t being an AR(1) process, respectively, M1 and M2 are given as

$$d_t^{M1} = \beta_0 + \beta_1 t + \psi^*(L)(\delta_1 DU'_{1,t} + \delta_2 DU'_{2,t}) \qquad (3.4)$$

$$d_t^{M2} = \beta_0 + \beta_1 t + \psi^*(L)(\delta_1 DU'_{1,t} + \delta_2 DU'_{2,t} + \kappa_1 DT'_{1,t} + \kappa_2 DT'_{2,t}) \qquad (3.5)$$

where $DU'_{1,t} = 1(t > T'_{B,i})$, $DT'_{1,t} = 1(t > T'_{B,i})(t - T'_{B,i})$, and $T'_{B,i}$, $i = 1, 2$ indicate break dates. Further, δ and κ represent the magnitudes of level and slope breaks, respectively. Also $\psi^*(L)$ ensures slow occurrence of breask over time in line with the innovative outlier (IO) framework.

It follows that the reduced-form regressions of the structural break models for unit roots can be given in (3.6) and (3.7) for M1 and M2, respectively as

$$y_t^{M1} = \rho y_{t-1} + \alpha_1 + \beta^* t + \delta_1 D(T_B')_{1,t} + \delta_1 DU'_{1,t-1} + \delta_2 DU'_{2,t-1} + \sum_{j=1}^{k} \beta_j \Delta y_{t-1} + \epsilon_t \quad (3.6)$$

$$y_t^{M2} = \rho y_{t-1} + \alpha^* + \beta^* t + \theta_1 D(T_B')_{1,t} + \theta_2 D(T_B')_{2,t} + \gamma_1 DU'_{1,t-1} + \gamma_2 DU'_{2,t-1} + v_1^* DT'_{1,t-1} + v_1^* DT'_{2,t-1} + \sum_{j=1}^{k} \beta_j \Delta y_{t-1} + \epsilon_t \quad (3.7)$$

A unit root test for null hypothesis is performed as $\rho = 1$ versus the alternative hypothesis of $\rho < 1$ from t-statistic of $\hat{\rho}$ in (3.6) (see Narayan and Liu, 2011; Narayan and Liu, 2015; Narayan et al., 2016; Narayan and Popp, 2010). Critical values for test statistic are given in Table 4 of Narayan and Popp (2010). The NP10 test has proven to have correct size, stable power, and identifies the structural breaks accurately Narayan and Popp (2010).

3.3.3 Volatility models

Last, to address the effect of presidential elections on the stock returns, we model the volatility across the sub-sample periods. This helps to examine the persistence and leverage effects during these times as a result of the disturbances in stock market. We have chosen to model the volatilities after determining break points instead of doing the two together. The reason is that simultaneously determining break points in the volatility models as seen in Narayan and Liu (2015); Narayan et al. (2016); Salisu and Fasanya (2013), etc. may compromise the power, size, and the accuracy of adequately identifying break points in the original series Narayan and Popp (2013).

To model the volatility, we employ the generalised autoregressive conditional heteroscedasticity (GARCH) model proposed by (Engle 1982) and (Bollerslev 1986). While studies such as Alagidede, Panagiotidis, and Zhang (2011), Appiah-Kusi and Menyah (2003), and Ntim et al. (2011) have found evidence of inefficiencies in African equity markets bordering on predictability of both returns and volatility, there is also some evidence showing that the stylised facts are conditionally varying (Alagidede and Panagiotidis, 2009; Piesse and Hearn, 2002; Tooma, 2003). This happens in the midst of global disturbances in developed markets which force investors to invest outside their borders for new opportunities (Korkpoe and Owusu Junior, 2018). The turbulence in the Tanzania stock market due to the presidential elections can be likened to the dynamics of financials market during turbulent times.

In the light of non-normalities, non-linearities, volatility clustering, and structural breaks in stock markets (Engle and Patton, 2007; Wang et al., 2001), the exponential GARCH (EGARCH) and Glosten, Jagannathan and Runkle GARCH (GJR-GARCH) have been espoused for use since they are in the asymmetric family of models (Alexander, 2008). In this study, we employ these together with the symmetric (standard)-GARCH to assess their performance in capturing the dynamics in the stock index.

3.3.3.1 The standard-GARCH (sGARCH)

The sGARCH is the simplest of the GARCH models. For a given return y_t as defined in 3.3.1, the conditional variance is given by

$$\varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2) \tag{3.8}$$

While the leverage effect in market requires that asset returns behave differently to price shocks in the market, the sGARCH assumes the response of the conditional variance is same for both negative and positive and thus symmetrical tails. The parameters are restricted as $\omega > 0$, $\alpha, \beta \geq 0$, $\alpha + \beta < 1$ are the conditional variance in (3.8) to remain positive for the sGARCH(1,1) which is given as

$$\sigma_t^2 = \omega + \alpha y_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3.9}$$

3.3.3.2 Exponential-GARCH (EGARCH)

The EGARCH is due to Nelson (1991) for the restrive nature of the non-negativity constraints in the sGARCH (Nelson and Cao, 1992). To capture leverage effect, an additional parameter γ is introduced as

$$ln(h_t) = \omega + \beta\, ln(h_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2/\pi} \right] \tag{3.10}$$

where $\omega, \alpha, \beta,$ and γ are constant parameters and have their usual meaning, and from Bollerslev, (1986) GARCH(p,q) as

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}, \tag{3.11}$$

where $\alpha_1, \dots, \alpha_p, \beta_1, \dots, \beta_q,$ and ω are constant parameters (Engle and Ng, 1993). The conditional variance is constrained to be non-negative by the axion that h_t is a function of the historical values of ε_t^2. Further, the error terms are parameterised as

$$\varepsilon_t = \varepsilon_{t-1}^2 (h_t)^{1/2}, t = 1, \dots, T \qquad (3.12)$$

It is clear from (3.10) γ is a function of both the magnitude and sign of ε_t^2 which enables h_t to respond asymmetrically to positive and negative values of ε_t. This is the appeal of the EGARCH model. The multiplicative term $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ ensures that the asymmetries in the returns are adequately captured. The coefficient γ is typically negative to ensure that positive return shocks induce less volatility than negative return shocks (Engle and Ng, 1993). For $\gamma < 0$, negative shocks have a bigger impact on future volatility than positive shocks of the same magnitude. This effect is often referred to as a "leverage effect" (Longmore and Robinson, 2004).

One advantage of the EGARCH(1,1) model over the sGARCH(1,1), for instance, is that we can analyse the effect of news on the conditional heteroscedasticty. This is important in the context of this study to analyse the impact of various news items surrounding the presidential elections and their impact on the stock index. For a constant $t - 2$ and ealier, we can examine the implied relation between ε_{t-1} and h_t called the 'news impact' curve, with all lagged conditional variances evaluated at the level of the unconditional variance of the stock index return. The curve is termed 'news impact' because it measures how new information is incorporated into volatility estimates, thus relating past return shocks (news) to current volatility (see Engle and Ng, 1993).

3.3.3.3 GJR-GARCH

The GJR-GARCH model (Glosten, Jagannathan, and Runkle, 1993) also belongs to the family of asymmetric GARCH models and allows the conditional variance to respond differently to the past negative and positive innovations. The GJR-GARCH differs from EGARCH with an extra parameter to capture leverage in the data series. The parameter γ ensures a specific way to enhance the volatility response to only adverse markets shocks. For $\varepsilon_t \sim GJR - GARCH$ if we can write $\varepsilon_t = \sigma_t z_t$, where z_t is standard Gaussian (for simplicity) and

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{[\varepsilon_{t-1}<0]} + \beta \sigma_{t-1}^2, \qquad (3.13)$$

where > 0 , $\alpha \geq 0$, $\alpha + \gamma \geq 0$ and $\beta \geq 0$, $I_{\varepsilon_t<0} = 1$ if $\varepsilon_t < 0$ and 0 otherwise. The model is sign-GARCH model because $I(.)$ denotes the indicator function. For equity returns, γ is typically found to be positive and thus the volatility increases more following negative shocks than positive shocks in proportion. In this model, good news, $\varepsilon_{t-1} > 0$ and bad news, $\varepsilon_{t-1} < 0$, have differing effects on the conditional variance. Good news has an impact of α while bad news has an impact of $\alpha + \gamma$. If $\gamma > 0$, bad news increases volatility, and there is a leverage effect for the i^{th} order in α_{t-1}. If $\gamma \neq 0$, the news impact is asymmetric Glosten et al. (1993). The news impacts are captured by (3.14) and (3.15)

$$h_t = A + \alpha\varepsilon_{t-1}^2, \forall\, \varepsilon_{t-1} > 0 \tag{3.14}$$

and

$$h_t = A + (\alpha + \gamma)\varepsilon_{t-1}^2, \forall\, \varepsilon_{t-1} < 0 \tag{3.15}$$

where $A \equiv \omega + \beta\sigma^2$ and σ is the unconditional standard deviation and ω is the constant term. In this study, we have chosen to limit the model orders to (1,1) as it is common in the literature. Among others, Brook & Burke (2003) show that the lag order (1,1) of GARCH models is sufficient to capture all of the volatility clusters in the data.

In all of the three models, we use the conditional skewed t distribution to correctly mirror the fat-tails which characterise the distribution of the returns in the data. Also, the estimations are done using the maximum likelihood approach (Malmsten, 2004). For all the three models, we use the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hannan-Quinn information criterion (HQIC) used to determine best fitting model for analysis inference. This approach has been well used in the literature (see Boako, Tiwari, and Roubaud, 2019; Chkir et al., 2020; Nikoloulopoulos, Joe, and Li, 2012; Shahzad et al., 2017); Yu et al., 2018). Lastly, the ARCH LM test is employed for post-estimation analysis to validate the models.

Chapter Four: Results and Discussion

4.1 Introduction

In this chapter, we present the empirical results and analysis from the tests conducted. The chapter starts with a preliminary analysis of the stock index which paves way for the subsequent empirical analysis. For a less robust assessment of the presidential election's impact, abnormal returns were calculated for the event window. Further, the Narayan and Popp (2010) unit root structural break test is employed as a robustness test for change in the stock market dynamics. Based on this outcome, the data are sub-sampled and volatility is modelled to determine the impact of the presidential elections on the stock market.

4.2 Preliminary analysis

4.2.1 Abnormal returns in the stock index

As mentioned earlier we estimate abnormal returns in the Tanzania stock market index based on the market model to provide an idea of effect of the electioneering activities on the stock market. Table 1 presents the test of significance for the abnormal returns within the (-5…+5) window for both nominations and election periods. Figures 2a and 2b also show the plots of these abnormal returns with the same window for the same periods. The results in Table 1 indicate that there is no statistical difference between the mean of the abnormal returns before the event date and that of the abnormal returns for nominations and election periods. This is not surprising given the small (-5…+5) window.

Table 1: Test of significance for abnormal returns

	Pre-nomination	**Post-nomination**	**Pre-election**	**Post-election**
t-test	-0.08358	0.17524	-0.14683	0.18343
p-value	0.936	0.8654	0.8875	0.859

In Figures 2a and 2b we find the different patterns of abnormal returns for both nominations and election periods. It is clear that abnormal returns are mostly bigger post-nomination through to the election periods. This also hints of structural breaks fostered by these activities. This is robustly tested in Section 4.3.

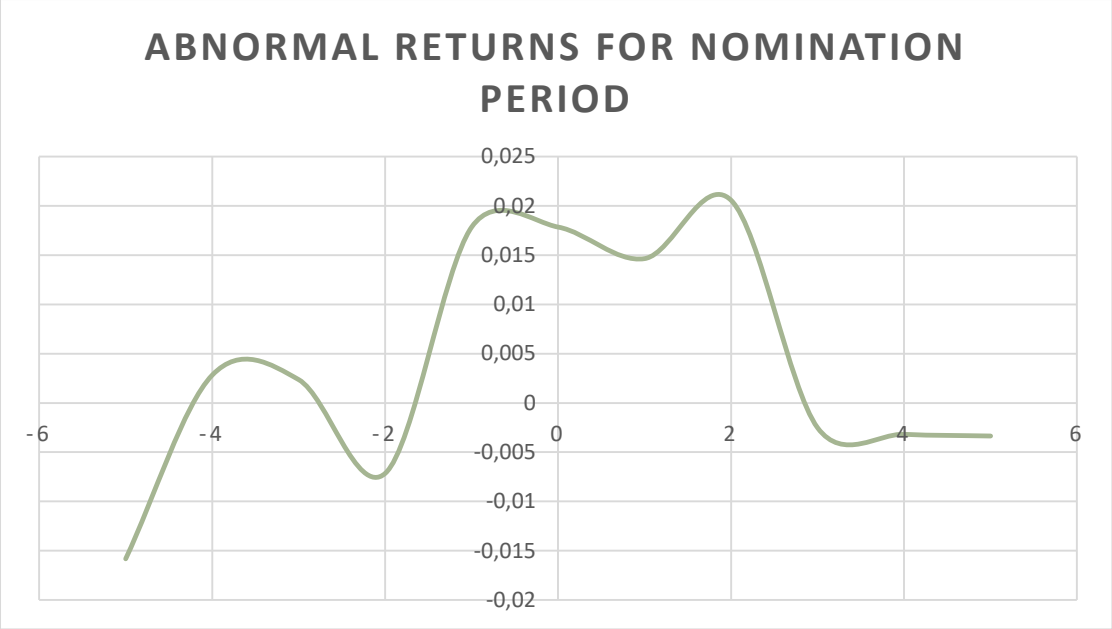


Figure 2a: Abnormal returns for pre-nominations and post--nominations in Tanzania stock market index

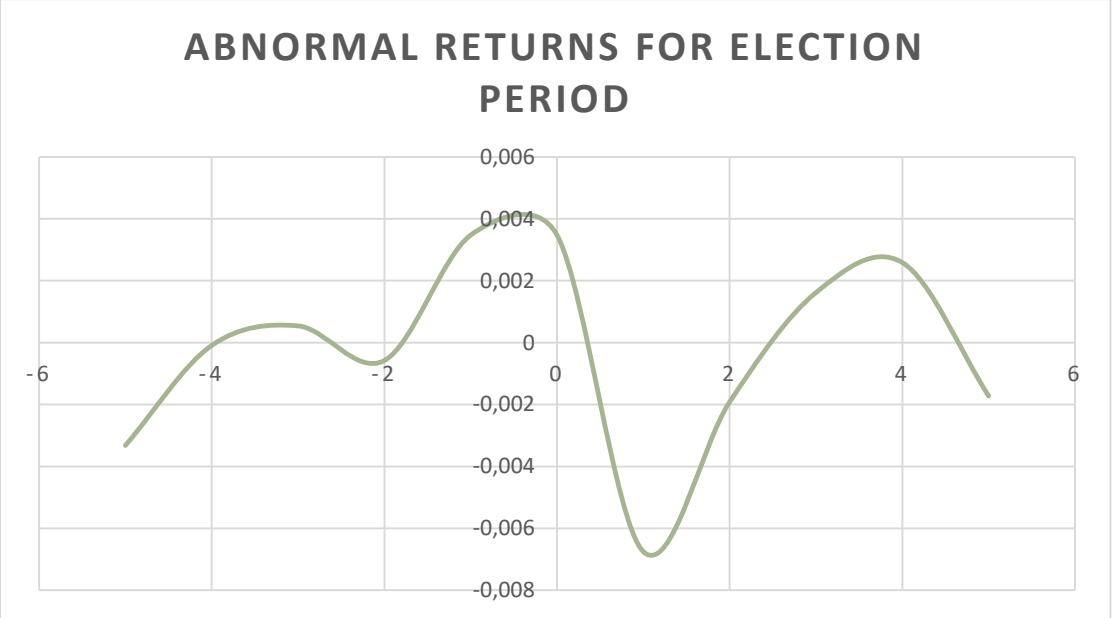


Figure 2b: Abnormal returns for pre-elections and post-elections in Tanzania stock market index

4.2.2 Descriptive statistics and ARCH effects

This section presents descriptive statistics of the stock market index. Based on the NP10 test and the sub-samples adopted for the rest of the study, we present description of the three sub-samples as well, namely; pre-break, break, and post-break periods. The pre-election, election, and post-election periods also fall within these time frames. The statistics are presented in Table 2 for each sub-sample period.

Table 2: Summary statistics

DSEI	Full sample period	Pre-break period	Break period	Post-break period
Mean	0.0000	0.0003	-0.0002	-0.0002
Standard Dev.	0.0141	0.0100	0.0173	0.0173
Skewness	0.3091	3.1923	0.3893	-0.1130
Kurtosis	26.3317	46.2354	16.4853	19.6722
p-value of JB*	(0.00)	(0.00)	(0.00)	(0.00)
p-value of ARCH LM	(0.00)	(0.00)	(0.00)	(0.00)
# of observations	2399	983	492	924

Note: JB indicates Jarque Bera test of normality; the hypothesis of normality is rejected at all conventional levels of significance.*

In Table 2, we find that means are very small considering the full sample and pre-break periods but negative (and small) considering the break and post-break periods. These suggest that investments in the stock market are either less rewarding or loss generating. It is hence important for detailed analysis of the price and return dynamics to be performed for prospective investors. The standard deviations are also mild; they are not far apart from each other ranging from 0.01 to 0.02 across the board and they show less volatility in the stock market. Nonetheless, this does not imply their impacts cannot be large. However, break and post-break averages are negative as compared to the other periods. These imply that negative returns dominate positive returns during the break period. It is not unusual for this to happen during a period of structural break, but that it continues after that implies that the market is still reeling of the uncertainties generated by the cause of structural breaks. Further, we observe left skewness in the post-break period as compared to the other periods which are all right-skewed. This implies the existence of extreme negative returns following the break that tend to pull the mean below zero as shown in the negative average value. Nonetheless, the right-skewness seem to be longer when they do occur. Thus, in the period when positive returns are obtained, they are bigger. This can bolster some level of confidence of investors with the hope to recover losses in the future.

In terms of the shape of the distribution of returns, we find all to be leptokurtic. This peakedness in the returns point to the non-normality behavior of stock market data. This is further corroborated by the Jarque Bera test of normality. It indicates rejection of normality as all conventional level of significance. Thus, regardless of whether the DSEI is experiencing

turbulence or tranquility, the returns deviate from normality, as should be expected of returns on a typical financial market asset.

Given that the study goes on to model volatility in these returns, we test for the presence of ARCH effects in the returns. We use the Engle (1982) ARCH Langrange Multiplier (LM) test. This test is based on the null hypothesis that there is no volatility in the return series. For p-value of 0.000 for all the series, we fail to accept that there are not ARCH effects. There is rather strong evidence of ARCH effects in the series. Therefore, we can confidently model volatilities as done in Section 4.5.

Table 3: Stationarity tests

DSEI		**Level (index values)**			**First difference (Index Returns)**	
	Test value	**Lag**	**P-value**	**Test value**	**Lag**	**P-value**
ADF	2.70	8	0.99	218.5	8	0.99
KPSS	0.278	11	0.01	0.123	11	0.09

For this event study and the Tanzania stock market index at the center, we do not expect the statistical properties of the series to remain constant over the full sample period; at least not for the price series. Hence, we employ two-unit root tests to test whether the series are stationary. These are the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shinn (KPSS) tests. While the two tests perform the same function, the KPSS is considered to have a higher power.

The ADF has a null hypothesis of non-stationarity while the KPSS has a null hypothesis of stationarity. From the outputs in Table 3, we observe that level, both tests reject stationarity in the series at 1% significance. Similarly, for the returns both tests confirm non-stationarity at the 1% significance level. While many financial time series are expected to be stationary at for returns, it is not surprising to find the Tanzania stock market index to be non-stationary at this point. Nonetheless, we have adopted a technique that deals well with modelling non-stationary returns series. In Section 4.4 and Table 4, using the Narayan and Popp (2010) (NP10), we have shown that there exist structural breaks in the series. It is also for this reason that the volatility modelling is done for the returns series in sub-samples as it pertains to the robust test of the structural breaks.

4.4 Robustness test: structural breaks

This section presents the robustness test of structural breaks in the Tanzania stock market index. The two structural break tests by Narayan and Popp (2010) are shown in Table 4 for the daily Tanzania stock market index. In line with NP10 the test assumes no break(s) under both the null and the alternative hypotheses of unit root. For models M1 and M2 test, statistics, break dates, and optimal lag lengths (k) are presented. The k values in NP2010 are obtained based on the procedure by Hall (1994). Further, T denotes the sample size and TB1 and TB2 denote the first and second structural break points (dates), respectively. Table 1 is analysed based on the 1 and 5 percent critical values of -4.672 and -4.081, respectively, in Narayan and Popp (2010). Our test rejects the null hypothesis that there is no unit root with two structural breaks at the 1% significance level.

Table 4: NP10 unit root test structural breaks test

		M1					**M2**			
		T	**Test statistic**	**TB1**	**TB2**	***k***	**Test statistic**	**TB1**	**TB2**	***k***
DSEI	04/01/2010 - 30/12/2019	2400	-2.957***	03/04/2014	31/03/2016	1	-3.484***	23/03/2012	03/04/2014	1

The series suffer two structural breaks under both models. The break dates in M1 are given as 03/04/2014 and 31/03/2016 for TB1 and TB2, respectively. On the other hand, break dates for M2 are 23/03/2012 and 03/04/2014, for TB1 and TB2, correspondingly. While we have argued for an exogenous event period beginning from 12th July, 2015 informed by the start of presidential elections campaign in Tanzania, the data and NP10 indicate otherwise. We find that the stock index experienced a structural break about a year before the start of election activities. It is clear from the data that during the start of the election activities there was heightened volatility in the market as seen in Figure 1 or 2. Therefore, we find that while the start of election activities did not create a new structural break, it intensified the volatility during this regime. The second break also occurred on 31/03/2016 which also corresponds with the trends in the price series. This seems to coincide with the break to revert the stock market to its past five-year trend.

Given that our initial study windows fall with these two structural break dates and they also have indicated impact on the stock market, we model volatility in the stock market using these break dates. That is to say we update the sub-sample periods for this study as follows: pre-

break period (04/01/2010 to 03/04/2014), break period (04/04/2014 to 31/03/2016), and post-break period (01/04/2016 to 30/12/2019). It is important to note that our initial sub-sampling based on the election activities fall within these new sub-sample periods based on the breaks. While they do not coincide, it is appropriate to model volatilities for these periods because they capture the original event periods for the study. We note that reference to "election period" has been used loosely to indicate the periods leading to the elections and the actual election periods. The study intends to examine how long news reflecting the volatilities of the stock market index persist. This will provide information for investors on the holding and selling out on their positions, among other things.

4.5 Volatility modelling: GARCH models

In this final section, we model the volatilities in the Tanzania stock market index for the full sample period as well as for the selected sub-sample periods based on the NP10 structural break test. This exercise provides a way to examine the impact of the presidential elections on the stock market. While investors aim for high returns, they come at the cost of high risk. Therefore, superior knowledge on the patterns of risk (as indicated by volatility) and how to model them is very important; it aids in effective decision making on the asset in question.

We have chosen to model volatility using the AR (1)-GARCH (1,1) for the standard, exponential and GJR in order to capture the persistence, asymmetry, and the impact of news in the stock returns. The AR (1)-GARCH (1,1) has been proven to adequately model the volatilities in asset returns. They are estimated by the maximum likelihood estimation and fitted with the student t distribution. The EGARCH and GJR-GARCH models have also been noted to have many advantages over the standard GARCH model. Further, models are chosen based on the least values of AIC, BIC, and HQIC (see Boako, Tiwari, and Roubaud 2019; Chkir et al. 2020; Nikoloulopoulos, Joe, and Li 2012; Shahzad et al. 2017; Yu et al. 2018). As mentioned earlier, we have also elected to model these sub-samples separately after determining break points instead of doing two together. The reason is that determining break points separately does not compromise the power, size, and the accuracy of adequately identifying break points in the original series (Narayan and Popp, 2013). The GARCH estimates and accompanying diagnostics are presented in Tables 5, 6, 7, and 8. Further, we have also shown that persistence is better examined when structural breaks and non-linearity are accounted for as done in this study (Bouri et al., 2018).

Table 5: Results of volatility models of the Tanzania stock market index for the full sample period

Full sample period			
Parameter/Model	**AR(1)-sGARCH(1,1)**	**AR(1)-EGARCH(1,1)**	**AR(1)-GJR-GARCH(1,1)**
Mean equation			
μ	0.0002 (2.04505)*	0.0001 (1.3945)	0.00016 (2.0451)*
$AR(1)$	-0.1747 (-8.4062)**	-0.1539 (-8.4127)**	-0.1747 (-8.40617)**
Variance equation			
ω	0.000001 (0.89911)	-0.2773 (-4.4489)**	0.0000 (0.89911)
α	0.1839 (5.1713)**	-0.0468 (-2.1469)*	0.1839 (5.1713)**
β	0.7969 (26.253)**	0.9686 (130.8699)**	0.7969 (26.2853)**
γ	0.0364 (1.0611)	0.3853 (16.3426)**	0.0364 (1.0611)
φ	3.4454 (19.6968)**	2.5057 (15.2948)**	3.4455 (19.6968)**
Persistence	0.9990	0.9686	0.9990
Half-life	692.7334	21.7108	692.7849
Observations	2399	2399	2399
Diagnostics			
AIC	-6.7529	-6.7780	-6.7529
BIC	-6.7360	-6.7611	-6.7360
HQIC	-6.7467	-6.7719	-6.7467
ARCH LM test (5)	0.3434 (0.9285)	0.2651 (0.9494)	0.34342 (0.9285)

Note: *, ** indicate 1% and 5% levels of significance, respectively. Values in parentheses are t-values for the coefficients and lag length for the ARCH LM test.

Table 6: Results of volatility models of the Tanzania stock market index for the pre-break sample period

Pre-break period			
Parameter/Model	**AR(1)-sGARCH(1,1)**	**AR(1)-EGARCH(1,1)**	**AR(1)-GJR-GARCH(1,1)**
Mean equation			
μ	0.0002 (2.0591)*	0.0001 (2.0138)*	0.0002 (1.9704)*
$AR(1)$	-0.1174 (-3.6229)**	-0.1134 (-5.9046)**	-0.1166 (-3.5908)**
Variance equation			
ω	0.0000 (1.1781)	-0.5390 (-2.7656)*	0.0000 (1.1559)
α	0.3273 (5.5106)**	-0.1169 (-2.3007)*	0.2939 (4.3243)**
β	0.6717 (11.1810)**	0.9446 (46.8832)**	0.6726 (10.9797)**
γ	-	0.4637 (3.0010)**	0.0651 (0.7227)
φ	3.0373 (13.6263)**	2.3759 (10.2295)**	3.0561 (13.4266)**
Persistence	0.9990	0.9446	0.9990
Half-life	692.6225	12.1532	692.6821
Observations	983	983	983
Diagnostics			
AIC	-7.9405	-7.9406	-7.9390
BIC	-7.9107	-7.9058	-7.9042
HQIC	-7.9292	-7.9273	-7.9258
ARCH LM test (5)	0.0983 (0.9871)	0.06626 (0.9926)	0.1024 (0.9864)

Note: *, ** indicate 1% and 5% levels of significance, respectively. Values in parentheses are t-values for the coefficients and lag length for the ARCH LM test.

Table 7: Results of volatility models of the Tanzania stock market index for the break sample period

Break period			
Parameter/Model	**AR(1)-sGARCH(1,1)**	**AR(1)-EGARCH(1,1)**	**AR(1)-GJR-GARCH(1,1)**
Mean equation			
μ	0.0002 (0.5231)	0.0004 (0.9807)	0.0003 (0.7291)
$AR(1)$	-0.1320 (-2.6643)*	-0.1114 (-2.3057)	-0.1348 (-2.7234)*
Variance equation			
ω	0.0001 (3.3548)**	-3.3562 (-3.8132)**	0.0001 (3.46045)**
α	0.5915 (3.0982)**	0.1524 (1.6668)	0.7373 (2.6795)*
β	0.2946 (3.2698)**	0.6018 (5.7791)**	0.2974 (3.4582)**
γ	-	0.8152 (5.1648)**	-0.2554 (-0.9601)
φ	3.2038 (6.1381)**	3.0040 (6.4933)**	3.2370 (6.1301)**
Persistence	0.8860	0.6018	0.9069
Half-life	5.7290	1.3651	7.0961
Observations	492	492	492
Diagnostics			
AIC	-5.9788	-5. 9730	-5.9768
BIC	-5.9276	-5. 9132	-5.9171
HQIC	-5.9587	-5.9495	-5.9534
ARCH LM test (5)	0.0790 (0.9906)	0.0467 (0.9955)	0.0816 (0.9901)

Note: *, ** indicate 1% and 5% levels of significance, respectively. Values in parentheses are t-values for the coefficients and lag length for the ARCH LM test.

Table 8: Results of volatility models of the Tanzania stock market index for the post-break sample period

Post-break period			
Parameter/Model	**AR(1)-sGARCH(1,1)**	**AR(1)-EGARCH(1,1)**	**AR(1)-GJR-GARCH(1,1)**
Mean equation			
μ	0.0000 (0.0126)	0.0001 (0.3093)	0.0000 (0.0031)
$AR(1)$	-0.1840 (-5.447)**	-0.19990 (-5.7056)**	-0.1839 (-5.4336)**
Variance equation			
ω	0.0000 (0.2010)	3.4141 (-3.9078)**	0.0000 (0.1940)
α	0.0145 (22.5509)**	0.0109 (0.1596)	0.0143 (2.3144)*
β	0.9845 (3426.9258)**	0.5934 (5.6980)**	0.9846 (2972.4518)**
γ	-	0.6793 (5.2309)**	0.0003 (0.0231)
φ	2.9334 (7.6053)**	2.7667 (9.3331)**	2.9358 (7.6098)**
Persistence	0.9990	0.5935	0.9990
Half-life	687.9727	1.3284	692.4493
Observations	924	924	924
Diagnostics			
AIC	-6.0222	-6.0652	-6.0201
BIC	-5.9909	-6.0286	-5.9835
HQIC	-6.0103	-6.0513	-6.0061
ARCH LM test (5)	0.1408 (0.9788)	0.3298 (0.9322)	0.1393 (0.9791)

Note: *, ** indicate 1% and 5% levels of significance, respectively. Values in parentheses are t-values for the coefficients and lag length for the ARCH LM test.

While all the three models for all the sub-samples, including the main sample, present interesting estimates on persistence in the volatility of the DSEI, we select only the best of each for further analysis. We do this using the information criteria. As a rule of thumb, the best model is the one with least information criteria value. Based on AIC, BIC, and HQIC, the AR(1)-EGARCH (1,1) is selected as the best fitting model for the full sample period. For the pre-break sample period, the symmetric AR(1)-sGARCH(1,1) is selected based on BIC and HQIC. Similarly, during the break sample period, the symmetric AR(1)-sGARCH(1,1) is best fitting as adjudged by all the information criteria. Lastly, the asymmetric AR(1)-EGARCH(1,1) model is selected for the post-break sample period.

It does emerge that the AR(1)-EGARCH(1,1) fits better for longer time series that the AR(1)-sGARCH(1,1). In light of the full sample period, we surmise that this study lends support to the EGARCH model as a better choice for modelling volatility across turbulent and tranquil market conditions. Salisu and Fasanya (2013) came to a similar conclusion for oil price volatility modelling. It is surprising to find that asymmetric AR(1)-GJR-GARCH(1,1) does not emerge as a best fitting model; any of the sub-samples contrary to it purported strength in fitting in extreme market conditions. Hence, the remainder of our analyses are based on the selected model in the respective sub-sample.

4.5.1 Persistence of volatility in the Tanzania stock market

Having accounted for structural breaks and non-linearity, it provide a better way to examine persistence (Bouri et al., 2019) as done in this Section. In simple terms, persistence shows how long volatilities decay after a shock (see Engle and Bollerslev, 1986; French, Schwert, and Stambaugh, 1987). To start with, all betas of all the selected models are statistically significant at the 1% level. This is important for the volatility models as the main parameter of concern. Alexander (2008), for instance, use the beta to measure persistence in GARCH models. The author advances that a beta of 0.9 or more suggests volatility has a slower reversion rate and hence persistent. Using this, it is observed that the period that experiences persistence in volatility is of full sample period with a beta of 0.9686. This comes as no surprise since we can see this from the price series plot in Figure 1 or 2. We observe in that dynamics that the index reverts to its prior five-year pattern after about three years of heightened volatility. This also confirms the non-stationary in the series as seen in Table 3. This is too long a time for any rational investor to wait and as such may serve a deterrent for investment interests in the DSEI because the presidential elections have sticky effects on the index.

However, Nelson (1991) presents better alternatives assessing persistence using the persistence and half-life measures. Persistence is defined as $(\alpha + \beta)$ while half-life is $ln(0.5)\,/ln(\alpha + \beta)$ (Nelson, 1991). Persistence is expected to be less than 1, so prediction of the volatility is not explosive. For a persistence of 1, the volatility has an exponential decay. Following these, we find that there are evidences of persistence in volatility for the three remaining sub-samples which would not be captured if only beta were used as an indicator of persistence.

From Tables 5, 6, 7, and 8, the persistence (half-life) are estimates as follows: full sample period, 0.9686 (22 trading days); pre-break sample period, 0.9990 (693 trading days); break sample period, 0.8860 (6 trading days); and post-break sample period, 0.5935 (less 2 trading

days). It is clear that the pre-break sample and full-sample periods have the longest persistence in volatility. It is not surprising given that the uncertainty surrounding presidential elections linger on until after the elections, which candidate wins, and what reforms they intend to undertake. The uncertain is often borne out of the contradictory campaign messages from the candidates. Hence, jumps in price volatility tend to be long-lived (Audrino and Hu, 2016) as seen in the DSEI. Persistence for 693 days out of 983 trading days is, however, unreasonable for the pre-break sample period. Another important note is that this portrays too much of market inefficiency since volatility during this period has too long a memory and can engender confident predictions in the market.

It is important to note that the pre break period contains the most number of observations in the sub sample period. It has been indicated above that the AR(1)-EGARCH(1,1) fits better for longer time series that the AR(1)-sGARCH(1,1); due to this reasoning the AR(1)-EGARCH(1,1) model is used for analysis for the pre break period. Persistence for 12 days out of 983 days appear more accurate and consistent with the patterns identified in Figure 1. The full-sample period of 22 trading days of persistence seems reasonable given at total of 2399 trading days. About a month is ample time to adjust portfolios even in very turbulent market conditions (Owusu Junior and Alagidede, 2020).

Out of 492 trading days in the break period, volatility jumps are short-lived for about 6 trading days. This is to say, the break period series has a short memory of about one week. Last, the post-break period shows the least of volatility persistence for about 2 trading days out of 924 trading days. This implies that volatility jumps are very short-lived and hence suggest a tranquil and efficient market period. In the context of this study, this is to be expected since the period is outside both the presidential nomination and election activities. We surmise, as also confirmed in the price series in Figure 1, that the Tanzanian economy is regaining the stability in the stock market that was thrown overboard by the elections. This is suggestive of the fact that confidence has been restored in the economy and the stock market as well. Levels of uncertainty have also been reduced for investment in the stock market index and its component stocks.

These levels of persistence for all the selected models and for the samples are corroborated by the conditional variances as can be seen in Figure 3. We can see how distinct the post-break levels of volatility are almost flat day-on-day (see blue line) as compared to the rest. This points to the short life span of volatility jumps in the post-break period for the DSEI.

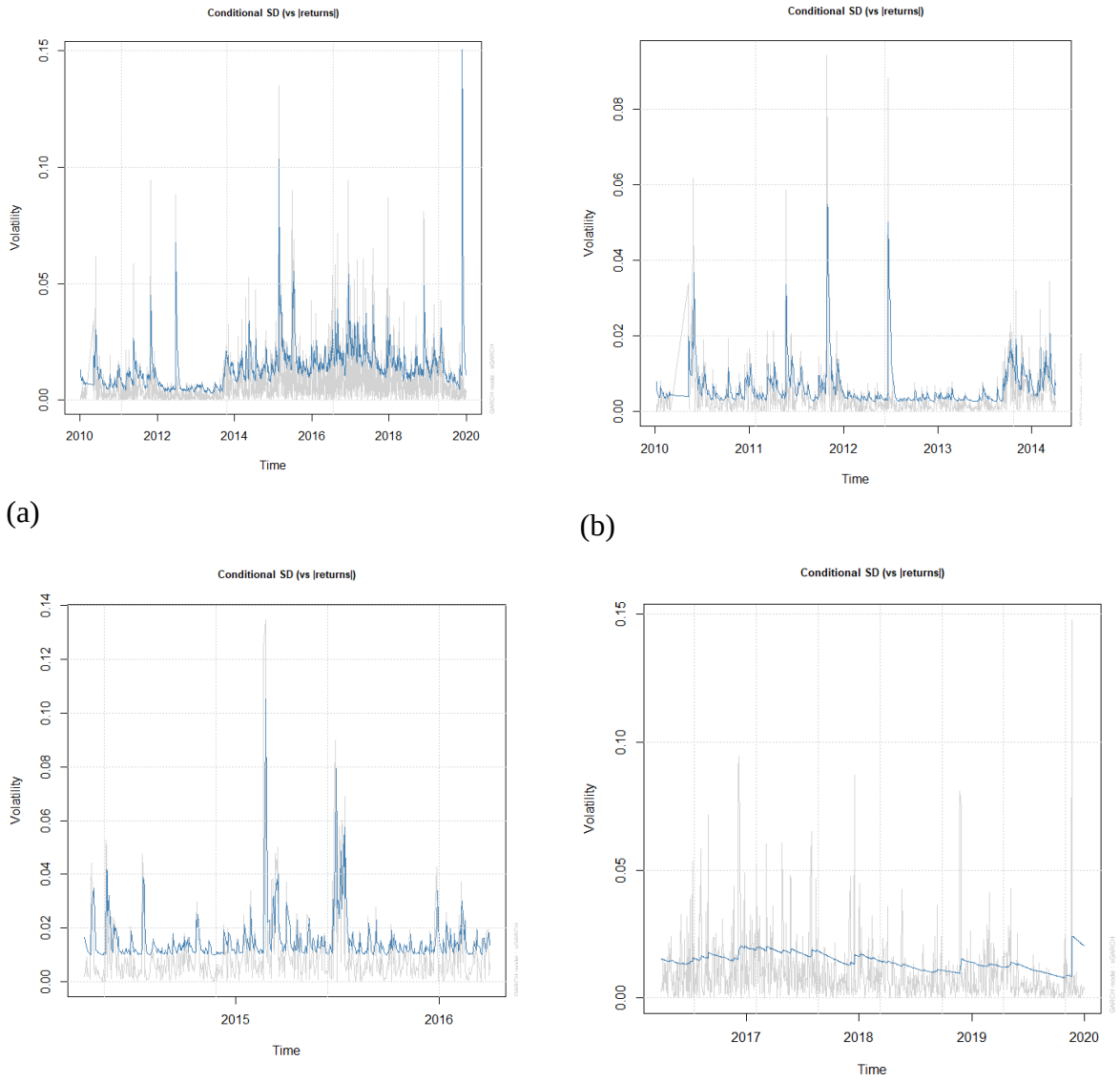


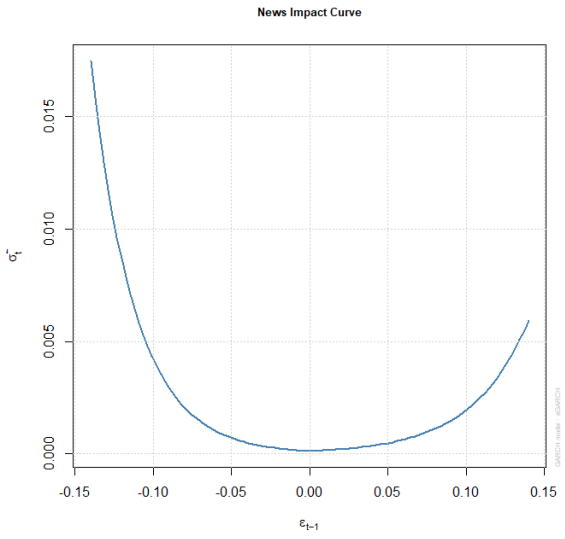
Figure 3: Conditional variance plots of the DSEI samples. Note: (a) - (EGARCH(1,1) for full sample period, (b) - sGARCH(1,1) for pre-break period, (c) - sGARCH(1,1) for break period, & (d) - EGARC(1,1))for post-break period.

4.5.2 News impact analysis in the Tanzania stock market

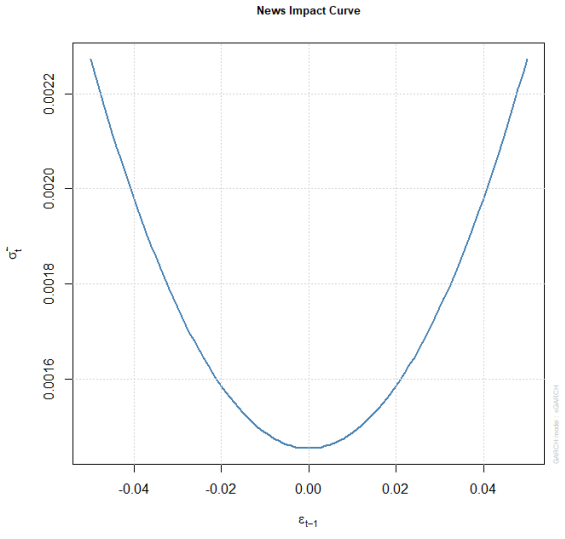
In Figure 4 we present the impact of good and bad news on volatility in the DSEI. In line with the extant literature, the sGARCH(1,1) does not distinguish between the impact of bad and good new as seen in the news impact curve in Figure 4. The curves are centered at $\varepsilon_{t-1} = 0$ with symmetry on both sides. These imply that there seems to be no difference in the impact of good and bad news on the volatility of the DSEI. Further, it implies that there is a reduced reaction to extreme news in general or unresponsiveness to extreme news given that that the $\gamma < 2$ (Robert and Victor, 1993) in break sample period (γ does not exist for the pre-break period). These two models do not help for the purposes of judging investment prospects in the

midst of presidential elections. These are real life situations which elicit varied reactions by stakeholders and hence differing impact on the stock market index. For instance, it is not expected that news arriving about monetary policy to increase the interest rate will have the same impact as reducing interest rate.

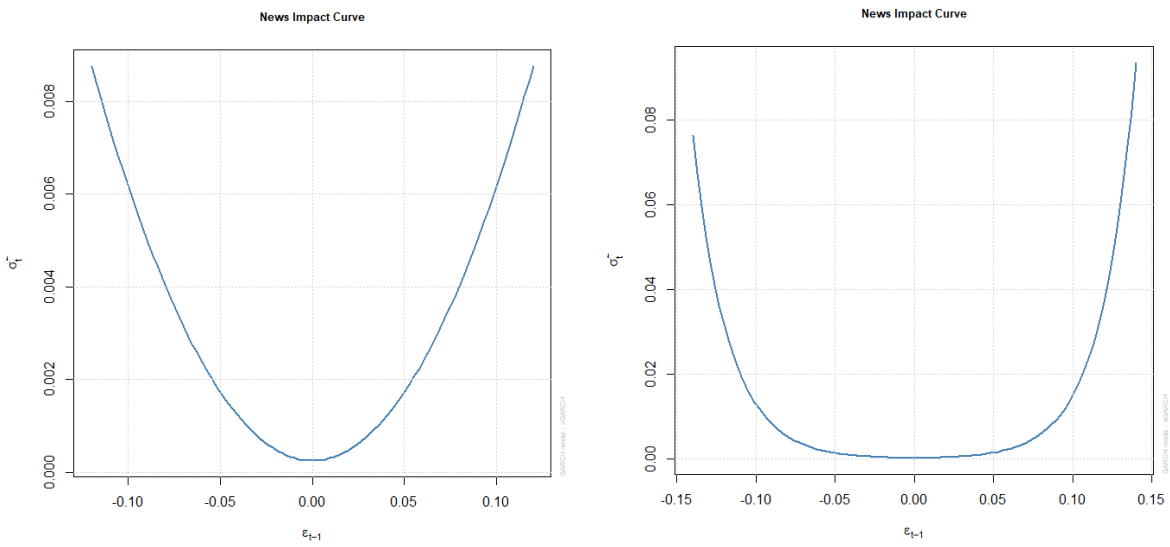
For the full and post-break sample periods, the EGARCH(1,1) present asymmetric news impact curve centered at $\varepsilon_{t-1} = 0$ with differing slopes on the positive and negative sides as postulated in (Glosten et al. 1993). These are a little steeper than the sGARCH(1,1) models, also corresponding to the extant literature. The difference in the lengths of the slopes also confirm that the models capture the asymmetry in the effect of news on the volatility of the DSEI returns. Further, while the responses are asymmetric, they are not pronounced as seen in the slopes. In the full sample period, the model captures more of the bad news than the good news with the opposite scenario in the post-break period. This make sense and also confirmed by the short life span of the persistence. This implies that news is received with more confidence and seen in a more positive lens than they would have been during the election periods. Furthermore, we surmise that the EGARCH(1,1) model is a better fit than the sGARCH(1,1) model to differentiate between the impact of good and bad news on the Tanzania stock market index.



(a)



(b)



(c) (d)

Figure 4: News impact curves for DSEI samples. Note: (a) - (EGARCH(1,1) for full sample period, (b) - sGARCH(1,1) for pre-break period, (c) - sGARCH(1,1) for break period, & (d) - EGARC(1,1))for post-break period.

4.5.3 ARCH LM diagnostics

In this final stage of the analysis, we intend to validate the selected GARCH(1,1) models using the ARCH LM test at lag 5 as seen in the last row of Tables 6, 7, 8, and 9. While, we did a pre-estimation examination of the presence of ARCH effects in the model, it also proper to examine the models have captured adequately these effects using the same test. At this post-estimation point, we expect the null hypothesis of no ARCH effects to be accepted since the models are supposed to capture these effects completely.

With a minimum of 0.93 p-value for all the models across the four sample, the ARCH LM test confirms that the models have almost completely captured all the ARCH effects in the DSEI series. We thus fail to reject the null hypothesis of no ARCH effects. The tests also fail to differentiate between the sGARCH(1,1) and EGARCH(1,1) models since they show the same conclusion at the same levels of confidence.

Chapter Five: Conclusion and recommendation for further studies

5.1 Conclusion

In this study we analyse for the first time the impact of the 2015 presidential election on the returns of the Dar Es Salaam Stock Market. There are a wide range of studies on the impact of presidential elections on stock market returns of many countries. Most of these studies have been conducted in developed nations, very little in Africa and no known study in Tanzania. As European economies are struggling with debt crisis and sluggish growth expected in the US, investors are eyeing African markets. Investors from outside the country have always played a large role in providing liquidity on the DSE (Nellor, 2008).

Stock markets play an important role in an economy; they enable companies to raise capital from the public, which enables them to expand their operations, and most importantly from a government point of view, pay more taxes and employ more people. Thus a well-functioning stock market is vital for economic development especially for developing countries such as Tanzania.

Our first important observation was reached by studying the daily returns on the Dar Es Salaam Stock market from the period of 4th January 2010 to 30th December 2019. The graphic presentation in Figures 1 show the behaviour of stock market return over time. It was further noticed that volatility clustering had increased over time compared to the period before 2014. This indicates an increase in the magnitude of volatility at DSE. Volatility of stock markets is one of the key issues that concern market participants. Highly volatile markets lower investor confidence. Abnormal returns computed in Figure 2a and 2b indicated different patterns of abnormal returns for both nomination and election.

The descriptive statistics based on the NP10 test and the sub sample indicates that the break and post break averages are negative compared to the pre-break period of positive returns. This implies that negative returns dominate positive returns in the respective periods. It not unusual for this to happen during a period of structural break, but that it continues after that to imply that the market is still reeling of the uncertainties generated by the presidential election activities. This further confirms that the effect of the elections has an impact and a sticky effect as they are still being felt. Market uncertainty still persist after the structural break. The post-break level of volatility was less compared to the break period

The findings from this study showed that the 2015 presidential elections had an effect on the returns of the Dar Es Salaam Stock Market. The study recommends that investors should

carefully plan and carry out investments during and after the period of general elections as returns could be affected either positively or negatively during the period. Efforts have been made by the government to encourage transparency, good corporate governance and economic empowerment via the listing of telecoms and mining companies that should optimistically lead to an increase in the vibrancy, depth and velocity of the market. Thus, attracting liquidity through new listings and market innovation should become an important task for the Dar Es Salaam Stock Exchange.

This analysis produces a deeper understanding into how election euphoria, can affect the whole financial system of an economy. Hence, policy makers will have the tools of deal with such situations more appropriately in order to safeguard the financial system as well as attract international equity investors to Tanzania. This is important because international investors are always on the look for diversifying into emerging and frontier markets at they have the promise of higher returns than advanced markets.

5.2. Recommendation for further studies

For further studies, it will be interesting to study the effect of the presidential elections on the returns of the different sectors individually listed on the DSE. This study can also be replicated for other indexes on the DSE once data becomes available for it.

Reference

Alagidede, Paul, and Theodore Panagiotidis. 2009. 'Calendar Anomalies in the Ghana Stock Exchange'. *Journal of Emerging Market Finance* 8(1):1–23.

Alagidede, Paul, Theodore Panagiotidis, and Xu Zhang. 2011. 'Why a Diversified Portfolio Should Include African Assets'. *Applied Economics Letters* 18(14):1333–40.

Alexander, Carol. 2008. *Market Risk Analysis, Practical Financial Econometrics*. Vol. II. West Sussex, United Kingdom: Wiley.

Aliyu, Shehu U. R. 2019. 'DO PRESIDENTIAL ELECTIONS AFFECT STOCK MARKET RETURNS IN NIGERIA?' 19(1):17.

Anyimadu, Adjoa. 2016. 'Politics and Development in Tanzania'. 38.

Appiah-Kusi, Joe, and Kojo Menyah. 2003. 'Return Predictability in African Stock Markets'. *Review of Financial Economics* 12(3):247–70.

Audrino, Francesco, and Yujia Hu. 2016. 'Volatility Forecasting: Downside Risk, Jumps and Leverage Effect'. *Econometrics* 4(1):8. doi: 10.3390/econometrics4010008.

Bamwenda, Emilia. 2018. 'The Symptoms of the Shift towards an Authoritarian State in Tanzania's President John Pombe Magufuli's Rule'. *Politeja-Pismo Wydziału Studiów Międzynarodowych i Politycznych Uniwersytetu Jagiellońskiego* 15(56):123–50.

Barberis, Nicholas, and Richard Thaler. 2003. 'A SURVEY OF BEHAVIORAL FINANCE'. *NATIONAL BUREAU OF ECONOMIC RESEARCH* 78.

Basdas, Ulkem, and Adil Oran. 2014. 'Event Studies in Turkey'. *Borsa Istanbul Review* 14(3):167–88.

Beaulieu, Marie-Claude, Jean-Claude Cosset, and Naceur Essaddam. 2005. 'The Impact of Political Risk on the Volatility of Stock Returns: The Case of Canada'. *Journal of International Business Studies* 36(6):701–18. doi: 10.1057/palgrave.jibs.8400160.

Bialkowski, Jedrzej, Katrin Gottschalk, and Tomasz Piotr Wisniewski. 2008. 'Stock Market Volatility around National Elections'. *Journal of Banking and Finance* 55.

Boako, Gideon, Aviral Kumar Tiwari, and David Roubaud. 2019. 'Vine Copula-Based Dependence and Portfolio Value-at-Risk Analysis of the Cryptocurrency Market'. *International Economics* 158:77–90.

Bollerslev, Tim. 1986. 'Generalized Autoregressive Conditional Heteroskedasticity'. *Journal of Econometrics* 31(3):307–27.

Bouri, Elie, Luis A. Gil-Alana, Rangan Gupta, and David Roubaud. 2018. 'Modelling Long Memory Volatility in the Bitcoin Market: Evidence of Persistence and Structural Breaks'. *International Journal of Finance & Economics* 0(0):1–15. doi: 10.1002/ijfe.1670.

Bouri, Elie, Luis A. Gil-Alana, Rangan Gupta, and David Roubaud. 2019. 'Modelling Long Memory Volatility in the Bitcoin Market: Evidence of Persistence and Structural Breaks'. *International Journal of Finance & Economics* 24(1):412–26.

Brooks, Robert D., Sinclair Davidson, and Robert W. Faff. 1997. 'AN EXAMINATION OF THE EFFECTS OF MAJOR POLITICAL CHANGE ON STOCK MARKET VOLATILITY: THE SOUTH AFRICAN EXPERIENCE'. 35.

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay. 2019. 'Event-Study Analysis'. *The Econometrics of Financial Markets* 149–80. doi: 10.2307/j.ctt7skm5.9.

Campbell, John Y., Andrew Wen-Chuan Lo, Archie Craig MacKinlay, and others. 1997. *The Econometrics of Financial Markets*. Vol. 2. princeton University press Princeton, NJ.

Campello, Daniela. 2009. 'Do Markets Vote? A Systematic Analysis of Portfolio Investors' Response to National Elections'. *Department of Politics, Princeton University, Mimeo*.

Chande, Risha. 2015. 'CCM Is Still the Most Popular Party in the Country'. *Taweza*. Retrieved (https://www.twaweza.org/).

Chau, Frankie, Rataporn Deesomsak, and Jun Wang. 2014. 'Political Uncertainty and Stock Market Volatility in the Middle East and North African (MENA) Countries'. *Journal of International Financial Markets, Institutions and Money* 28:1–19. doi: 10.1016/j.intfin.2013.10.008.

Chkir, Imed, Khaled Guesmi, Angham Ben Brayek, and Kamel Naoui. 2020. 'Modelling the Nonlinear Relationship between Oil Prices, Stock Markets, and Exchange Rates in Oil-Exporting and Oil-Importing Countries'. *Research in International Business and Finance* 101274.

Dangol, Jeetendra. 2006. 'Unanticipated Political Events and Stock Returns: An Event Study'. 86–110.

DSE. 2019. *Dar Es Salaam Stock Exchange Market Report*.

Engle, Robert F. 1982. 'Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation'. *Econometrica: Journal of the Econometric Society* 987–1007.

Engle, Robert F., and Tim Bollerslev. 1986. 'Modelling the Persistence of Conditional Variances'. *Econometric Reviews* 5(1):1–50.

Engle, Robert F., and Victor K. Ng. 1993. 'Measuring and Testing the Impact of News on Volatility'. *The Journal of Finance* 48(5):1749–78.

Engle, Robert F., and Andrew J. Patton. 2007. 'What Good Is a Volatility Model?' Pp. 47–63 in *Forecasting volatility in the financial markets*. Elsevier.

Eriksen, Stein Sundstøl. 2018. 'Tanzania: A Political-Economy Analysis'. 46.

Fama, Eugene F. 1970. 'Efficient Capital Markets: A Review of Theory and Empirical Work'. *Journal of Finance* 25(2):383–417.

French, Kenneth R., G. William Schwert, and Robert F. Stambaugh. 1987. 'Expected Stock Returns and Volatility'. *Journal of Financial Economics* 19(1):3.

Füss, Roland, and Michael M. Bechtel. 2008. 'Partisan Politics and Stock Market Performance: The Effect of Expected Government Partisanship on Stock Returns in the 2002 German Federal Election'. *Public Choice* 135(3–4):131–50. doi: 10.1007/s11127-007-9250-1.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle. 1993. 'On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks'. *The Journal of Finance* 48(5):1779–1801.

Guney, Yilmaz, and Gabriel Komba. 2016. 'Testing for the Weak-Form Market Efficiency of the Dar Es Salaam Stock Exchange'. *Handbook of Frontier Markets* 3–26. doi: 10.1016/B978-0-12-803776-8.00001-X.

Hadi, Mahdi M. 2006. 'Review of Capital Market Efficiency: Some Evidence from Jordanian Market'. *International Research Journal of Finance and Economics* 3(3):13–27.

Hall, Alastair. 1994. 'Testing for a Unit Root in Time Series with Pretest Data-Based Model Selection'. *Journal of Business & Economic Statistics* 12(4):461–70.

Hasan, Kaya. 2004. *Electoral Violence, Political Stability and the Union in Tanzania*.

Kabiru, James Ndungu, Duncan Elly Ochieng, and Hellen Wairimu Kinyua. 2015. 'THE EFFECT OF GENERAL ELECTIONS ON STOCK RETURNS AT THE NAIROBI SECURITIES EXCHANGE'. *European Scientific Journal* 11:26.

Kahneman, Daniel, and Andamos Tversky. 1973. 'ON THE PSYCHOLOGY OF PREDICTION'. *Psychological Review* 80(4):15.

Katabi, Maximillian Michael, and Gwahula Raphael. 2018. 'An Emprical Analysis of Weak-Form Efficiency of Dar Es Salaam Stock Exchange'. 6(2).

Kim, Harold Y., and Jianping P. Mei. 2001. 'What Makes the Stock Market Jump? An Analysis of Political Risk on Hong Kong Stock Returns'. *Journal of International Money and Finance* 20(7):1003–16. doi: 10.1016/S0261-5606(01)00035-3.

Korkpoe, Carl H., and Peterson Owusu Junior. 2018. 'Behaviour of Johannesburg Stock Exchange All Share Index Returns-An Asymmetric GARCH and News Impact Effects Approach'. *SPOUDAI-Journal of Economics and Business* 68(1):26–42.

Kothari, S. P., and Jerold B. Warner. 2007. *Econometrics of Event Studies*. Vol. 2. Woodhead Publishing Limited.

Li, Jinliang, and Jeffery A. Born. 2006. 'Presidential Election Uncertainty and Common Stock Returns in the United States'. *Journal of Financial Research* 29(4):609–22.

Lyimo, Karl. 2015. 'Tanzanian Election Opinion Polls a Political Trojan Horse'. *The Citezen*.

Malmsten, Hans. 2004. *Evaluating Exponential GARCH Models*. SSE/EFI Working paper Series in Economics and Finance.

Mendelson, Morris, and Sidney Martin Robbins. 1976. *Investment Analysis and Securities Markets*. Basic Books (AZ).

Menge, Robert Nyamweya. 2013. 'Effect of Elections on Stock Market Returns at the Nairobi Securities Exchange'. 74.

Narayan, Paresh Kumar, and Ruipeng Liu. 2011. 'Are Shocks to Commodity Prices Persistent?' *Applied Energy* 88(1):409–16.

Narayan, Paresh Kumar, and Ruipeng Liu. 2015. 'A Unit Root Model for Trending Time-Series Energy Variables'. *Energy Economics* 50:391–402.

Narayan, Paresh Kumar, Ruipeng Liu, and Joakim Westerlund. 2016. 'A GARCH Model for Testing Market Efficiency'. *Journal of International Financial Markets, Institutions and Money* 41:121–38.

Narayan, Paresh Kumar, and Stephan Popp. 2010. 'A New Unit Root Test with Two Structural Breaks in Level and Slope at Unknown Time'. *Journal of Applied Statistics* 37(9):1425–38. doi: 10.1080/02664760903039883.

Narayan, Paresh Kumar, and Stephan Popp. 2013. 'Size and Power Properties of Structural Break Unit Root Tests'. *Applied Economics* 45(6):721–28.

Narayan, Paresh Kumar, and Susan Sunila Sharma. 2015. 'Does Data Frequency Matter for the Impact of Forward Premium on Spot Exchange Rate?' *International Review of Financial Analysis* 39:45–53.

Nellor, David CL. 2008. 'The Rise of Africa's "Frontier" Markets'. *Finance & Development* 45(3):30–33.

Nelson, Daniel B. 1991. 'Conditional Heteroskedasticity in Asset Returns: A New Approach'. *Econometrica: Journal of the Econometric Society* 347–70.

Nelson, Daniel B., and Charles Q. Cao. 1992. 'Inequality Constraints in the Univariate GARCH Model'. *Journal of Business & Economic Statistics* 10(2):229–35.

Nguthi, Paul Ndung'U. 2013. 'The Effect Of Political News On Stock Market Returns In Kenya: The Case Of March 2013 General Elections'. 64.

Niederhoffe, Victor, Stevens Gibbs, and Jim Bullock. 1970. 'Presidential Elections and the Stock Market'. *Financial Analysts Journal* 2:111–13.

Nikoloulopoulos, Aristidis K., Harry Joe, and Haijun Li. 2012. 'Vine Copulas with Asymmetric Tail Dependence and Applications to Financial Return Data'. *Computational Statistics & Data Analysis* 56(11):3659–73.

Njuguna, Josephine. 2016. 'The Market Efficiency of the Tanzania Stock Market'. *Banks and Bank Systems* 11(3):75–86. doi: 10.21511/bbs.11(3).2016.08.

Ntim, Collins G., Kwaku K. Opong, Jo Danbolt, and Frank Senyo Dewotor. 2011. 'Testing the Weak-Form Efficiency in African Stock Markets'. *Managerial Finance* 37(3):195–218.

Obradović, Saša, and Nenad Tomić. 2017. 'The Effect of Presidential Election in the USA on Stock Return Flow – a Study of a Political Event'. *Economic Research-Ekonomska Istraživanja* 30(1):112–24. doi: 10.1080/1331677X.2017.1305802.

Pástor, Ľuboš, and Pietro Veronesi. 2013. 'Political Uncertainty and Risk Premia'. *Journal of Financial Economics* 110(3):520–45. doi: 10.1016/j.jfineco.2013.08.007.

Piesse, Jenifer, and Bruce Hearn. 2002. 'Equity Market Integration versus Segmentation in Three Dominant Markets of the Southern African Customs Union: Cointegration and Causality Tests'. *Applied Economics* 34(14):1711–22.

Robert, Engle, and Ng Victor. 1993. 'Measuring and Testing the Impact of News on Volatility'. *The Journal of Finance* 48(5):1749–78.

Ross, Stephen A., Randolph Westerfield, and Bradford D. Jordan. 2008. *Fundamentals of Corporate Finance*. 5th ed. Tata McGraw-Hill Education.

Salisu, Afees A., and Ismail O. Fasanya. 2013. 'Modelling Oil Price Volatility with Structural Breaks'. *Energy Policy* 52:554–62.

Shahzad, Syed Jawad Hussain, Safwan Mohd Nor, Ronald Ravinesh Kumar, and Walid Mensi. 2017. 'Interdependence and Contagion among Industry-Level US Credit Markets: An Application of Wavelet and VMD Based Copula Approaches'. *Physica A: Statistical Mechanics and Its Applications* 466:310–24.

Soultanaeva, Albina. 2008. *Impact of Political News on the Baltic State Stock Markets*. Umeå University, Department of Economics.

Tooma, Eskandar A. 2003. 'Modeling and Forecasting Egyptian Stock Market Volatility before and after Price Limits'. Economic Research Forum Cairo.

Tsay, Ruey S. 2005. *Analysis of Financial Time Series*. Vol. 543. John wiley & sons.

Valadez, Ray M. 2012. 'The U.S. Presidency and the Stock Market: A Political Relationship Study of the Market Performance'. 13.

Wang, Kai-Li, Christopher Fawson, Christopher B. Barrett, and James B. McDonald. 2001. 'A Flexible Parametric GARCH Model with an Application to Exchange Rates'. *Journal of Applied Econometrics* 16(4):521–36.

Wanjiru, Ngigi Rosemary. 2000. 'The Impact Of Fiscal And Monetary Policies On Stock Market Performance In Kenya: An Empirical Analysis.' 74.

Westerlund, Joakim, and Paresh Narayan. 2013. 'Testing the Efficient Market Hypothesis in Conditionally Heteroskedastic Futures Markets'. *Journal of Futures Markets* 33(11):1024–45.

Yu, Wenhua, Kun Yang, Yu Wei, and Likun Lei. 2018. 'Measuring Value-at-Risk and Expected Shortfall of Crude Oil Portfolio Using Extreme Value Theory and Vine Copula'. *Physica A: Statistical Mechanics and Its Applications* 490:1423–33. doi: 10.1016/j.physa.2017.08.064.

Zainabu, Zuwena. 2014. 'An Assessment of the Effect of General Elections on the Stock Market Returns in Kenya'. 68.

Zuravicky, O. 2005. 'The Stock Market: Understanding and Applying Ratios, Decimals, Fractions, and Percentages'. *New York: The Rosen Publishing Group*.