Foreign Portfolio Equity Flows in Selected Sub-Saharan Africa Countries: The Underlying Process, Impact on Stock Market Capitalisation, and Policy Options

By

FRANCIS ZIWELE MBAO
MBXFRA001

SUBMITTED TO THE UNIVERSITY OF CAPE TOWN
In fulfilment of the requirements for the degree of
Doctor of Philosophy (PhD) in Finance

Department of Finance and Tax
Faculty of Commerce
University of Cape Town

March 2021

Supervisors:
A/Professor Francois Toerien (PhD)
Department of Finance and Tax, University of Cape Town, and
Dr Maxwell Chibelushi Musongole (PhD)
University of Lusaka

Plagiarism Declaration

I, Francis Ziwele Mbao, do hereby declare that the work presented in this thesis is my own, except where acknowledged, and that it has been submitted to the Turnitin module. I confirm that the Turnitin report has been discussed with my supervisor and that there are no unresolved concerns emanating from this thesis. In addition, this thesis, or any part of it, has not been previously submitted for the award of a degree at any university.

Abstract

The volatility of capital flows and their adverse impact on macroeconomic and financial variables is a major concern to policy makers, resulting in a debate on whether capital controls or financial (capital account) liberalisation is best suited to managing them. This study argues that a better understanding of the underlying process of the foreign capital flows, that is, whether they are a random walk, a persistent, or an anti-persistent series, is a critical but currently lacking element in informing this debate. Specifically for foreign portfolio equity flows, there may also be need to understand their dynamic impact on stock markets. The purpose of this study is therefore to determine the underlying process of foreign portfolio equity flows in the sub-Saharan Africa countries for which a sufficiently long data series is available (*i.e.*, Kenya, Nigeria, South Africa, and Zambia); to establish the impact of these flows on the capitalisation of their stock markets; and draw conclusions on optimal policy choices based on this.

Secondary monthly data, covering the period January 1994 to March 2019, is used, but with different sample periods for each country within that range. Structural break estimations are further undertaken to obtain more specific results. Fractal analysis is employed to estimate the Hurst parameter, a measure of the underlying process. This is aided by fractal signal classification, adopted from electronic and communication engineering and physiology, a novel approach in the analysis of capital flows, to avoid misinterpreting the estimated Hurst parameter. The *correlation measure* technique, another novelty in the analysis of foreign capital flows, is also used to further understand the underlying process of the flows. Bayesian techniques based on sign restrictions are employed in estimating the *Calderon-Rossell* model, a unique approach, to establish the impact of these flows on stock market capitalisation. The robustness of the results is tested with the Fry and Pagan Median target method.

The results indicate that the underlying process of gross foreign portfolio equity inflows and outflows in the four sub-Saharan Africa countries are anti-persistent. Further, increases in market capitalisations owing to positive shocks to foreign portfolio equity inflows are greater than declines resulting from shocks to outflows. The policy implication of these results for the four SSA countries is that capital controls on foreign portfolio equity flows are redundant.

Dedication

To my Lord, whose name I always call upon because it is my strong tower, all I can state is Ebenezer; to my mum, *Witness Mwale-Mbao,* and my late dad, *Watson Mbao*, you shaped me in my young life; and to my late uncle, *Paul William Mwale*, the man who brought me up and died a month after completing my undergraduate degree, your investment was not in vain, and thank you so much.

Acknowledgements

The successful completion of this thesis could hardly be realistic without the assistance and support from a lot of individuals. In this regard, first and foremost, with sincerity and gratitude of heart and due respect, I would like to say thank you to *Dr. Francois Toerien*, Associate Professor, my supervisor, from the Department of Finance and Tax at the University of Cape Town. This is for his frankness and sincerity in guiding that this project attains the standard of a PhD work. Thanks for coming through and rescue this project at a time when there was no one to provide mentorship and supervision. God bless you! Thank you also for accepting that *Dr. Maxwell Chibelushi Musongole* comes on board as a co-supervisor. At this point let me also thank *Dr. Musongole* for the critical technical mentorship that helped shape the project. Thank you for introducing me to the world of *Chaos theory* and *Fractal geometry*. Gratitude also goes to *Dr Chipo Mlambo* for the opportunity to enroll on the PhD programme. Your initial guide set the path open for this achievement. Sincerely grateful for your effort and opportunity to work with you.

Gratitude and thanks also go to *Dr. Francis Chipimo*, former Director of Economics Department and now Deputy Governor – Operations at the Bank of Zambia, my employer. Words are not enough, and my expression may not be visible, but God knows my heart and how full it is with gratitude for your unwavering support to this cause. God bless you too!

Big thank you and appreciation are in order to *Dr Jonathan Chipili*, Director of Economics Department, Bank of Zambia. Your constant reminder that I was a student and that I needed not to overload myself with extra assignments since you took over as Director of the Economics Department in August 2019 helped me to stay focused on the academic project. It is not easy to write a PhD whilst doing full time work. The attention can be divided and slows down someone. Thanks also go to Dr Noah Mutoti for initiating me into the world of *Bayesian econometrics*.

Thanks, and appreciations are also in order in respect of the colleagues: *Kafula Longa, Kamwi Mulele, Patrick Mulenga* and *Wakumelo Mata* for that quick glance and checking of some chapters to ensure that the message being communicated is clearly understood by the reader. This is in addition to checking for spelling and grammatical errors; and *Joseph Simumba, Dr Frank Chansa,* *Kafula Longa* and *Keegan Chisha* for some technical discussions. To *Peter Zgambo*, thanks for that nomination to attend a seminar on *Applied Bayesian econometrics for central bankers* at the Bank of England. It broadened my understanding and application of Bayesian Techniques in empirical work. This academic project benefited hugely from that seminar.

Gratitude equally goes to *Apostle Dr Collins C. Chipaya*, my spiritual father, of Revival Fire Missions International and *Prophet Bob Ngolela* of Amen Christian Church, Cape Town, for the spiritual uplifting. A PhD project is an undertaking that needs support from all angles depending on one's inclination. It can at times be emotionally draining and most of the time mentally challenging. A word of assurance is such a valuable support to continue with an academic argument on a consistent path. Thanks for the words of encouragement and spiritual support.

Last, and not by any mean the least, is my gratitude to *Dorothy*, my beloved wife, one of my greatest achievements, and good friend. The one year I was away for my course work, you played the role of both a mother and a father to our lovely children – *Baraka, Zawadi, Mkindi* and *Lusungu*. God bless you and favour you! You are a Proverb 31 woman my beloved Dottie. And to our children, thanks for bearing my long hours of working on this project depriving you of father-children interaction. God bless you All and may He show you his Glory!

Table of Contents

List of Tables

List of Tables in the Appendices

List of Figures

Chapter 1
Introduction and Background

1.1. Introduction

This chapter provides the background information to this study, which focuses on the underlying process of foreign portfolio equity flows and their impact on the stock market capitalisation in selected sub-Saharan Africa (SSA) countries, namely, Kenya, Nigeria, South Africa, and Zambia. In addition, this study further explores the optimal policy option(s) for these countries given the lack of consensus on whether capital controls[1] or financial liberalisation is the suitable policy for managing foreign capital flows.

1.2. Background Information

Foreign private capital flows are part of global foreign financial flows. These flows are divided into three broad classes; foreign direct investments (FDI), foreign portfolio investments (FPI), and bank flows (Salacuse, 2017 and Kirabaeva and Razin, 2010). FDI is an investment stake of at least ten percent of the outstanding shares in a given domestic firm by a non-resident investor (IMF, 2009). FPI can take the form of equity or debt, with equity investments (i.e. foreign portfolio equity flows, FPEF) being less than a ten percent holding of the total outstanding shares of a given company (Salacuse, 2017 and IMF, 2009). Portfolio debt flows are largely investments in and out of government securities in SSA countries.

Foreign capital flows offer benefits, but can also create risks to recipient countries, and in this regard raise important policy issues (Koepke, 2019; and Ostry et al., 2011). This concern has once again come to the fore following the dramatic reversal of foreign portfolio flows in emerging and frontier market economies amidst the COVID-19 pandemic shock (IMF, 2020). A retrenchment of approximately US $100 billion worth of foreign portfolio equity flows in emerging markets in a period before September 2020, following the COVID-19 shock, has been estimated (Kalemli-ozcan, 2020). This magnitude of outflows underscores the anxieties associated with foreign capital flows whenever there is a shock.

[1] Capital controls is some form of restrictions on transactions on cross border assets (Pasricha, 2017).

After liberalisation of capital accounts[2] and undertakings of financial sector reforms by most emerging and frontier market governments, stock markets have become one of the major channels for foreign capital flows into emerging and frontier markets[3] (Montiel and Reinhart, 1999; Edison and Warnock, 2003; and Bekaert and Harvey, 2003). In the past, foreign portfolio investments in SSA – save for South Africa – was small compared with flows into other emerging markets (Moss et al., 2007). However, there have been signs of growing investor interest, especially during the period just before the global financial crisis (Massa and Macias, 2009) and after 2010, following the recovery from the global financial crisis (Hussain et al., 2014). Araujo et al. (2015) observed an increase in non-FDI private flows to frontier market economies, including those in Africa. Given the trend towards deeper integration with global financial markets, SSA emerging and frontier financial markets are likely to become increasingly vulnerable to global financial shocks (Hussain et al., 2014), given the fickle behaviour of these flows, including foreign portfolio equity flows (Eichengreen et al., 2017 and Bluedorn et al., 2013).

Since stock markets are one of the major channels for foreign portfolio investments in sub-Saharan Africa, this may also impact its stock markets' capitalisation, as for example shown through mathematical modelling in Chapter 5 of this thesis, via the inflow and outflow of such funds. Foreign portfolio equity flows affect stock markets' valuations through the changes to their market capitalisations. Therefore, depending on the nature of shocks to the FPEFs, this may possibly also pose financial market governance challenges, in addition to adverse macroeconomic outcomes. Inflows may inflate stock prices because they augment demand. Consequently, they may contribute to improving investment return (capital gain) through stock price increases. Inflows may also lead to exchange rate appreciation, and in turn lead to a downward inflation bias. However, outflows may exert downward pressure on stock prices, thereby contributing to the decline in stock market capitalisation and development, for the affected markets. The outflows could also contribute to foreign exchange rate volatility with a bias towards depreciation, and hence broader economic effects including rising inflation.

---

[2] This process is referred to as financial openness, as well as capital account or financial liberalisation.

[3] However, this may be true only when crisis periods are disregarded, as observed by McQuade and Schmitz (2017).

Foreign portfolio equity flows may be beneficial by providing liquidity in stock markets (Levine, 1997), as potential sellers of stocks can find buyers, particularly for Sub-Saharan African stock markets, which are generally regarded as relatively illiquid (Gourène et al., 2018; Boako and Alagidede, 2018; and Yartey and Adjasi, 2007). Foreign portfolio equity flows may also help to integrate the SSA stock markets, particularly outside South Africa, with global financial markets, as the former are regarded to be financially relatively less integrated with global financial markets compared to other frontier and emerging market stock exchanges elsewhere (Kablan and Kaabia, 2018). Therefore, creating a conducive environment for attracting more foreign portfolio equity inflows into the sub-Saharan Africa region can help develop its stock markets (Yartey and Adjasi, 2007). On the other hand, because SSA stock markets may offer relatively high returns (Gourène et al., 2018) and, generally, diversification opportunities (Zaremba and Maydybura, 2019), African equity markets are potentially interesting to foreign investors. This could provide a mutual benefit of enhancing liquidity in the SSA stock markets and higher returns to foreign investors.

Nevertheless, the volatility of foreign capital flows in general, and foreign portfolio equity flows in particular, as well as their tendency to suddenly stop or reverse have created concerns in emerging and frontier markets, including those in sub-Saharan Africa. As a result, this has stimulated research and policy debates (Pasricha, Falagiarda, Bijsterbosch, and Aizenman, 2018a) including recent findings on the subject matter as documented by Guichard (2017). Capital flows have been studied from several perspectives and for various reasons (Mercado, 2019), including matters related to policy issues around foreign capital flows. For example, at the moment one of the policy issues regarding capital flows is whether or not capital controls should be used to stem these flows following the global financial crisis of 2008/09 (Boero et al., 2019 and Guichard, 2017)[4], given that they are in many respects quite fickle (Eichengreen et al., 2017 and Bluedorn et al., 2013).

However, there exists a dichotomy of views in the literature on policy orientation towards foreign capital flows. Specifically, this is regarding the desirability of implementing

[4] This includes the taper tantrum of 2013, and the monetary policy normalisation by the United States Federal Reserve Bank in 2015, which are more recent events of concern in this regard.

capital controls, as opposed to allowing financial liberalisation and using alternative capital management techniques that accompanies capital account liberalisation (Guichard, 2017).

This polarisation of views may be due to lack of a clear understanding of the underlying process of each type of these foreign private capital flows as well as how past and current events and behaviour related to these flows affect future flows. Notably for foreign portfolio equity flows, a lack of understanding of how a shock to this class of foreign capital flows propagates over time in impacting stock market development, specifically in the context of stock markets capitalisation, may further perpetuate this debate on foreign portfolio equity flows.

The International Monetary Fund (IMF) now seems to be recommending the use of capital controls to stem capital outflows under certain circumstances[5] (IMF, 2012). In addition, based on a panel study of almost 150 countries, Furceri and Loungani (2018) found that capital account liberalisation imposes welfare costs on countries.

However, those in favour of capital account liberalisation contend that it is a corollary of economic development and maturation as evidenced by high income countries that largely have no capital control measures in place (Eichengreen, 2001b). It is also argued that the lack of capital controls may help with efficient resource allocation both globally and domestically, in addition to helping diversify risk and deepening domestic financial markets (Ellyne and Chater, 2016). Bhatia and Sharma (2019) further found empirical evidence of capital account liberalisation being beneficial to both developed and developing countries generally.

In spite of this, Claessens et al. (1995) argues that without an understanding of the underlying process of foreign equity portfolio flows, it may be difficult to conclude whether capital controls should be imposed, or alternatively whether capital account liberalisations should be embraced.

[5] Ostry et al. (2011) have in this regard spelt out some circumstances and conditions that may warrant imposition of capital controls.

Notwithstanding the conflict of ideas stated above, when foreign portfolio equity flows, like any other class of foreign capital flows, are taken as a sequence of real numbers in physical space (time) and spectral space (frequency), they can be analysed with a view of understanding their underlying properties, which, in turn, can inform an appropriate policy response to these flows. Time series data have been found to be made up of the underlying signal which involves periodic variations and noise (see for example Khelifa, Kahlouche, and Belbachir, 2012), but often the underlying process is hidden and what is observed may largely be the noise. Therefore, an understanding of the underlying process of the time series data of foreign portfolio equity flows may be useful in determining its behaviour based on its hidden properties. This, in turn, may provide insight on whether the series can be predicted if it is not a random walk process, and whether it may thus be controlled.

Empirical literature on capital flows, including foreign portfolio equity flows, has mainly focused on their determinants; volatility; capital controls or, conversely, capital account liberalisation; and their impact on macroeconomic variables, but much less on the underlying process of these flows, resulting in findings having a limited link to policy formulation related to their management.

Studies on the determinants of capital flows, including foreign portfolio equity flows, are far more numerous in the literature[6] than those related to their underlying process. Researchers identified both pull (attractive conditions in recipient countries) and push (unfavourable conditions in countries of origin) factors as driving capital flows, including trade in financial services, domestic credit ratings, black market exchange rate premiums, interest rates, and real economic activity. With regard to volatility of these flows, it is believed that both short and long-term capital flows are prone to volatility. However, the liberalisation of financial services trade, with its attendant diversity of instruments, has been widely perceived to lead to less distorted and less volatile capital flows (Kono and Schuknecht, 1998). Meanwhile in SSA, global liquidity was found to induce foreign

[6] See, for example, Asiamah et al. (2019), Grigorian (2019), Lafuerza and Servén (2019), Hlaing and Kakinaka (2019), Vo (2018), Fedderke and Liu (2002), Kono and Schuknecht (1998), Taylor and Sarno (1997) and Fernandez-Arias (1996), who all investigate the determinants of these flows for developed, emerging, and developing countries, including sub-Saharan Africa countries.

portfolio equity flow volatility, while financial openness was associated with increased volatility (Opperman *et al*., 2017), and nothing said about their underlying process.

The lack of understanding of the role of long-range dependency (the underlying process) in these flows is not trivial for the purpose of policy consideration. Bruno et al. (2017)'s insight that some classes of foreign capital flows, bond flows in particular, go through some boom episodes which then reverse under their own weight (i.e. without policy intervention) may suggest that foreign capital flows have an inherent process that causes them to rise and after some time decline. Establishing the underlying process of these flows can therefore help to understand whether the pattern of rise and fall takes place within a relatively short period (the case of short-range dependence), or over a longer period (the case of long-range dependence). The underlying behaviour of foreign capital flows fitting the latter may require greater policy intervention than one related to short range dependence.

A few studies, such as those of Ning et al. (2017) and Bluedorn et al. (2013), do examine the underlying process of capital flows, but are based on consolidated data (either gross inflows, gross outflows and net-flows, or just the latter) of developed, emerging, and other developing countries. Therefore, no country-specific insights can be drawn from their results. Other studies of this type include those of Becker and Noone (2009), with a focus on selected developed and emerging market economies, but excluding those from sub-Saharan Africa; and Sarno and Taylor (1999a), with a focus on Latin American and Asian developing countries only. These too have left a gap with regard to the understanding of the nature of the underlying process of the foreign portfolio equity flows associated with sub-Saharan African countries specifically.

Although the line of inquiry in these studies was diverse, it was generally aimed at establishing issues of persistence, multifractal behaviour (the possibility of having a mixture of persistence and anti-persistence at different times in a given time series), or the permanence of the effects of shocks on foreign capital flows. Different estimation methods were used, including autoregressive analysis, autocorrelation analysis, state space methods, variance ratio analysis, and fractal analysis. The results to date are mixed.

Thus, some studies found capital flows to be persistent,[7] while others found them to be anti-persistent[8], which again underscores the need to explore the underlying process of these flows using different methods, potentially including non-parametric and non-linear approaches. Particularly for sub-Saharan Africa, previous studies have not been helpful in understanding the underlying flow behaviour for individual countries since the data from these countries, as stated earlier, were consolidated with that of others around the world with similar structural characteristics. In this regard, it is important to understand the nature of the underlying process of the foreign capital flows to individual sub-Saharan Africa countries, which will help inform the type of policy to pursue given the developmental role these flows can play in each sub-Saharan Africa market.

Non-parametric and non-linear methods employed in exploring the underlying process, such as that used by Ning et al. (2017), need to be augmented by fractal signal classification estimations aimed at establishing whether the foreign capital flows are a fractional Brownian motion (fBm) or a fractional Gaussian noise (fGn). This avoids the possible spurious interpretation of fractal analysis results as advised by Cannon et al. (1997), Eke et al. (2002), and Serinaldi (2010). Fractal analysis is one of the procedures for determining the underlying process of a time series by way of long-range dependence based on the value of the estimated Hurst parameter. The general practice in economics and financial literature is to perform a fractal analysis without undertaking estimations for fractal signal classification to determine whether the series in question is the fBm or fGn signal[9]. Failure to undertake fractal signal classification may, however, cast doubt on the validity of the results of the estimated Hurst coefficient (Serinaldi, 2010).

In considering the impact of capital flows, and particularly how foreign portfolio equity flows impact on stock market development, studies by Yartey (2008); Kemboi and Tarus (2012); Chukwuemeka et al. (2012); Eniekezimene (2013); and Nyaga (2017) are useful guides. However, although these studies investigate the relationship between foreign

[7] See for example Hiremath and Kattuman (2017) on India and Froot et al. (2001) covering 44 countries.

[8] Example includes Sarno and Taylor (1999a) on Asian and Latin America countries, Sarno and Taylor (1999b) on East Asian countries in addition to Australia and Japan and Cai, Dang and Lai (2016) on China.

[9] See, for example, Nguyen et al. (2019); Ning et al. (2017); Gyamfi et al. (2016); Lahmiri (2015); Sensoy and Tabak (2015), and Kristoufek and Vosvrda (2013), among others, who all used fractal analysis on economic and finance data without undertaking fractal signal analysis.

portfolio equity inflows or their net-flow counterparts and stock market development indicators in SSA, they do not estimate or show how the impact of shocks to inflows (or indeed net-inflows) dynamically propagate over time, and how such propagations affect stock markets. In addition, these studies largely focus on using gross foreign capital inflows or net-inflows as one of the determinants of stock market capitalisation, but neglect to determine the impact of the gross foreign equity portfolio outflows (FPEO) on stock markets' development. However, as pointed out by Eichengreen, Gupta, and Masetti (2017), gross capital outflows need to be considered too given their roles in economies, not least because of the possibility of the *flight to safety* phenomenon resulting in outflows whenever there is an adverse internal or external shock on a developing country economy (Yang et al., 2019; Alley and John, 2017; and Cerutti et al., 2017).

Although studies on capital flows have generally ignored the gross foreign portfolio outflows (Guichard, 2017), the focus on both gross inflows and outflows is nonetheless gaining momentum. Thus, a number of recent studies have focused on both gross inflows and outflows, examples being those of Broner et al. (2013); the IMF (2016); Eichengreen et al. (2017); Eichengreen, Gupta, and Masetti (2017); and Lafuerza and Servén (2019).

As this study focuses on foreign portfolio equity flows and stock markets[10], it should be noted that in most studies stock market capitalisation is used as a measure of stock market development[11]. Unlike stock market turnover, which is also used as a measure of stock market efficiency[12], stock market capitalisation when taken as a percentage of GDP, is also used as an indicator of a given country's financial market deepening (Cave, Chaudhuri and Kumbhakar, 2019; and Ho, 2019). Additionally, stock market capitalisation is used as a proxy for stock market development, unlike other stock market indicators, because it is less arbitrary (Garcia and Liu, 1999), meaning its variations may not be at the whim of chance and randomness. A rise or fall in stock market capitalisation

[10] This is because it is imperative to understand capital flows by sector since responses to shocks differ (Kalemli-ozcan, 2020).

[11] See, for example, Osaseri and Osamwonyi (2019); Pan and Mishra (2018); Sukcharoensin and Sukcharoensin (2013); and Yartey (2010).

[12] For instance as by Cave, Chaudhuri and Kumbhakar (2019).

may therefore have implications on the overall stock market valuation and financial sector depth, and thus stock market development.

1.3. Statement of the Problem

In view of the dichotomy of ideas and lack of consensus on how to control or manage foreign private capital flows, there is a need to understand the underlying process of these flows, and also to understand how the past and current behaviour of these flows have a bearing on future flows for optimal policy decision on the matter. There is scant understanding of the underlying process of the foreign portfolio equity flows in sub-Saharan Africa. Previous studies have not addressed specific sub-Saharan Africa countries at individual level but have included them in groups of similar countries from around the world, even though the extent of the effect of these flows may differ from one country to the next. Further, there is a lack of understanding of how past and current events of these flows affect future flows to and from sub-Saharan Africa. This knowledge is useful not only with the predictability of the behaviour of these flows, particularly in terms of direction and how likely that may last once the flows are affected by shocks, but also in reinforcing the understanding of their underlying process.

Additionally, particularly for foreign portfolio equity flows to and from sub-Saharan Africa, there is also a need to understand their dynamic impact on stock markets since it is essential to understand capital flows behaviour by class given that responses to shocks associated with these flows may not be homogenous (Kalemli-ozcan, 2020). African stock markets need foreign portfolio equity flows to help augment their liquidity. However, there is little understanding of the dynamic impact of shocks to the flows linked to sub-Saharan Africa, specifically in terms of how long the effects of such shocks last on the foreign portfolio equity flows themselves. This also extends to how such shocks impact sub-Saharan African stock markets' capitalisations, and thus stock market development, particularly in terms of their magnitude and the time it takes for the effect of the shock to dissipate.

Previous studies have estimated the impact of capital flows on stock markets based on the estimated parameter values and their "signings", i.e., positive or negative. While this approach generally establishes that foreign capital flows impact sub-Saharan African stock markets positively given the positive signs of the estimated parameters, it does not indicate how long it takes for a shock to foreign portfolio equity flows impacting sub-Saharan Africa stock markets.

In this regard, this study seeks to explore and establish the underlying process of foreign portfolio equity flows for both gross inflows and gross outflows. This study specifically takes into account fractal signal classification of each type of flows. In addition, the research also aims to ascertain whether current and past events related to these flows have a bearing on their future behaviour. This is necessary in the sense that it reinforces the understanding of the underlying process through its signing of being positive (indicating persistence) or negative (implying anti-persistence). This empirical analysis is achieved by computing the *correlation measure*, a technique that utilises the Hurst parameter's information estimated by fractal analysis.

The research also seeks to estimate the dynamic impact of these flows on stock market development and thereby ascertain the extent of the impact of shocks to foreign portfolio equity flows on selected sub-Saharan Africa stock markets' capitalisation. Bayesian techniques with sign restrictions are used to achieve this, as these techniques are suitable for short data series, which is the case with the data for some of the selected countries. Sign restrictions have an advantage over zero restrictions, an alternative estimation procedure, because unlike the zero restrictions they do not impose hard restrictions on the relevant economic theory.

1.4. Study Objectives

The objectives of the study are:

i. To establish the underlying processes of the gross foreign portfolio equity inflows and outflows for the sub-Saharan Africa countries of Kenya, Nigeria, South Africa and Zambia, by also considering structural breaks, if they exist, in each of the series;

ii. To determine whether past and current events of foreign portfolio equity flows have an influence on the future behaviour of these flows, in order to further understand the underlying process of the foreign portfolio equity flows in the four countries; and

iii. To establish the dynamic impact of the gross foreign portfolio equity inflows and outflows on the selected sub-Saharan Africa stock markets;

1.5. Research Questions

To satisfy the objectives above, the following research questions guide the study:

i. What is the underlying process of the gross foreign portfolio equity inflows and outflows data in a sample of sub-Saharan Africa countries?

ii. Do past and current events of gross foreign portfolio equity inflows and outflows impact future events related to the foreign portfolio equity flows in these sub-Saharan African countries, and what does this mean in terms of the underlying process of this class of foreign capital flows?

iii. How do shocks to gross foreign portfolio equity inflows and outflows affect stock market capitalisation? This is in the context of how long such impulses last in affecting the stock market capitalisation of each of these selected sub-Saharan Africa equity markets.

iv. In view of the above, what policy insights can be drawn from the results obtained by addressing these questions and be applied as optimal policy interventions for each of the selected sub-Saharan Africa countries given the dichotomy of views on foreign capital flows?

In providing answers to the research questions above, this thesis relies on secondary time series data, and it is therefore an exclusively quantitative methods-based research undertaking.

1.6. Scope of the Research

The study focuses on Kenya, Nigeria, South Africa, and Zambia. The choice of these countries is primarily due to their roles in the region, as well as the availability of suitable data. Thus, South Africa has the biggest stock market in Africa (Donou-Adonsou, 2019), while Kenya, Nigeria and Zambia are among the main frontier markets in Africa, and are thus of interest to global investors. In addition, Zambia has an open capital account as it is fully liberalised (Ellyne and Chater, 2016), while Kenya and Nigeria are among the countries with relatively bigger stock markets in Africa (Donou-Adonsou, 2019) and among Africa's top frontier markets (Ellyne and Chater, 2016). Further, for these four SSA countries, high frequency data are available on foreign portfolio equity flows for a relatively long time period of over five years, without gaps in the respective series. This is not the case for most other SSA countries with stock markets.

Kenya's Nairobi Securities Exchange automated trading in 2010 and has consistent monthly data on equity portfolio flows from 2011. Zambia has had an automated trading system right from inception of its securities exchange in 1994, and data on foreign portfolio equity flows are available on a monthly basis from 1997. Therefore, data from these two countries can be considered to be reliable. Nigeria's monthly data is consistent from March 2013. Even though South Africa only automated its equity trading in June 1996, data on foreign portfolio investors trading activities was regularly captured and reported to the South African Reserve Bank with a monthly frequency dating as far back as January 1992.

1.7. Novelty and Contribution

This study provides noteworthy contributions and extends the current literature on capital flows in general and foreign portfolio equity flows in particular by estimating the underlying process of capital flows based on the long-range dependence using the mono-fractal analysis, but considering structural breaks in the data in addition to fractal signal classification. To the author's knowledge no previous study has undertaken an estimation of the long-range dependence on foreign capital flows associated with Sub-Saharan Africa countries and elsewhere to establish their underlying process, and further accounting for structural breaks in the flows, including their fractal signal classification. The fractal signal classification is adopted from physiology, and electronic and communication engineering, and this study represents, as far as the author is aware, the first application of the technique to capital flows.

More importantly, the results from the fractal signal classification, which establishes whether the flows are either of the fBm or fGn type of signal have established how important it is to undertake such an estimation, given that the data for some variables in this study are seemingly persistent (and yet inherently stationary), which is indicated by the slowly decaying autocorrelation functions (ACF) and unit root tests indicating the series to be integrated of order one, as well as the estimated Hurst parameter being greater than 0.5. The use of fractal signal classification can thus be complimentary to unit root tests for establishing whether a series is stationary (integrated of order zero) or persistent (integrated of order one) or indeed having an order of integration which is not of the integer order. It thus contributes also to the literature on unit root tests, which has a bearing on the empirical methods to use when estimating time series data.

In addition, using the *correlation measure* results that are based on the estimated Hurst parameter, this study establishes whether past or current events of portfolio equity flows have a bearing on the future occurrence of these flows to reinforce the understanding of the underlying process of the foreign portfolio equity flows in the four sub-Saharan Africa countries. This is not found in prior literature on portfolio flows for sub-Saharan Africa in general, or indeed elsewhere. The significance of this is that the Hurst exponent estimation results may be incorporated in the forecasts of any time series economic and finance data. This is in the context of incorporating such information when imposing judgement on the forecasts generated by other methods. For example, if the data used for generating forecasts is an anti-persistent process, if that is what the value of the estimated Hurst exponent depicts, this means that the direction of the data series changes quite often in terms of its rise and fall. Therefore, forecasts based on such underlying data may be adjusted accordingly to ensure the anti-persistence behavior in the forecasted values and may therefore help in reducing some forecasting errors. The case should also apply for the persistent and random walk processes. In this regard, this study equally contributes to the literature on forecasting.

Similarly, this study contributes to existing empirical finance and economic literature on the interpretation of the Hurst parameter by applying fractal signal classification to capital flows data, at least for sub-Saharan African data, so as to establish whether its flows are either of the fBm or fGn type of signal. This avoids a possible spurious interpretation of the estimated Hurst parameter, because the same value of the Hurst parameter can belong to either an fBm or fGn signal. This approach is so far not available in the literature on foreign capital flows, and on foreign portfolio equity flows in particular. It is also scantly used in economics and empirical finance. It may therefore relates and contributes to the literature on, for example, the efficient market hypothesis (EMH) or its variant - the random walk hypothesis (RWH) – assessed on the basis of the estimated Hurst parameter. In the absence of knowledge of the fractal signal classification of the data used to establish the EMH or RWH behaviour, the conclusion held may need to be revisited as a robustness check. It also contributes to the literature on empirical finance and economics on issues related to carry trades and commodity trading returns, and the behaviour of macroeconomics variables assessed using the Hurst parameter, with an advice that the interpretation of the Hurst parameter should be done in line with the fractal signal classification results to ensure robustness of the results obtained given findings in this study.

Likewise, using empirical information based on signal classification of foreign portfolio equity flows, their underlying process, and impulse responses from the impact assessment of these flows on stock market capitalisation, this study contributes to the policy debate in literature on whether capital controls should be used to stem these flows in the countries under study, namely Kenya, Nigeria, South Africa, and Zambia with a conclusion that capital controls of foreign portfolio equity flows may not be optimal in the four countries as the results from this study suggest. Therefore, it is imperative as a matter of knowledge that policy (even investment) decisions should not be influenced by noise (what is observed) but by the underlying signal (what may not be observed) for optimal results.

Equally, this study contributes to the literature by extending the Bayesian Model Averaging work of Ng, Ibrahim and Mirakhor (2016), specifically by employing Bayesian techniques with sign restrictions to estimate the *Calderon-Rossell* model (Calderon-Rossell, 1991 and 1990) to not only show how a shock to foreign portfolio equity flows propagates over time through an impulse response function, but also how it affects stock market development via its market capitalisation. Specifically, it does so not just in magnitude and direction (as is common in literature) but also in time space, which represents a novel contribution. In previous studies, the *Calderon-Rossell* model was estimated using Bayesian Model Averaging (BMA), with a focus only on the FDI (see Ng, Ibrahim and Mirakhor, 2016), Panel Regression of the random/fixed effects model (for example by Sezgin and Atakan, 2015), the vector error correction mechanism (VECM) (for example by Churchill, Arhenful and Agbodohu, 2013), and the dynamic Generalised Methods of Moment (GMM) (for example by Yartey, 2008). These studies did not estimate or show how shocks to foreign portfolio equity flows evolve in time space, and how their impact on stock markets may evolve over time.

Further, the sign restrictions used in estimating the *Calderon-Rossell* model on gross foreign portfolio equity inflows and outflows, as well as stock market capitalisation, uses information obtained from a mathematical derivation on the relationship between foreign portfolio equity flows and stock market capitalisation, in Chapter five, that also renders support towards the development of a formal theory on gross foreign portfolio equity inflows/outflows and stock market capitalisation behaviour that is currently seems to be lacking in literature. This is a novel approach as previous studies have not relied on a formal relationship involving these two sets of variables. This study, therefore, contributes towards developing a formal theory on the impact of foreign portfolio equity flows on stock market capitalisation.

In summary, this study shows how estimates on the underlying process of foreign portfolio equity flows, for the first time using fractal signal classification techniques on foreign portfolio equity data as well as using fractal analysis, and estimating their impact on stock market capitalisation by applying the Bayesian techniques with sign restrictions on the Calderon-Rossell model, another first such action to the author's knowledge, can be used to generate information that can guide with policy choice on foreign portfolio equity flows. In literature, estimates on the underlying process of foreign portfolio equity flows have rarely been used to influence policy options, and estimates on the impact of foreign portfolio equity flows on stock markets have not in the past demonstrated how the shocks to market capitalisation evolve in time space to inform policy options, as is the focus of this study.

1.8. Structure of the thesis

This thesis is divided into six chapters, with Chapter 1 being the introduction and background to the study. Chapter 2 discusses the literature relevant to the study, and covers the theoretical and empirical literature on capital flows, their underlying processes and estimation procedures, the attendant need for fractal signal classification before undertaking estimations, the impact and estimation procedures of capital flows on stock markets' capitalisation, including the *Calderon-Russell* Model adopted for this study, and the possible candidate variables for estimating the impact of gross foreign portfolio equity flows on stock markets' capitalisation. Chapter 3 describes and visually plots the data used in this study, determines, and identifies structural breaks in the foreign portfolio equity inflows and outflows using basic statistical tests on the entire sample, as well as, where possible, for the periods before and after structural breaks, and presents descriptive statistics on all variables used. Various statistical tests are also described that give preliminary information on the nature of the dependence in the foreign portfolio equity inflow and outflow data.

Chapter 4, the first of the two empirical chapters, discusses the methodology and results of the empirical exploration of the underlying process of gross foreign portfolio equity inflows and outflows for Kenya, Nigeria, South Africa, and Zambia. The methodology used and discussed include Detrended Fluctuation Analysis (DFA) as well as the Wavelet Transformation Analysis to estimate the Hurst exponent, the fractal signal classification estimation procedure based on the periodogram of the power spectral density, and the *correlation measure* derived from the estimated Hurst parameter. Chapter 5, the second empirical chapter, covers methodology and results of the empirical assessment of the impact of gross foreign portfolio equity inflows and outflows on stock market capitalisation within the modified *Calderon-Rossell* model using the Uhlig (2005) penalty – function, a Bayesian vector autoregression (VAR) with sign restriction method. Lastly, in Chapter 6, the results, and the conclusion together with contributions of this study to knowledge and theory, as well as its policy implications, are summarised and discussed, and limitations and areas for future research are presented.

Chapter 2
Survey of the Literature

2.1. Introduction

In this chapter, the literature on the merits and demerits of capital controls and financial liberalisation, including literature on the current policy debate regarding foreign portfolio flows management, is discussed. Equally, the theoretical and empirical literature on capital flows, with the latter focusing also on the underlying process of capital flows and its long-range dependence and estimation procedures associated with the Hurst statistic, the determinants and volatility of these flows, and their impact on stock market capitalisation, is covered. Further literature discussed relate to the interaction of foreign portfolio equity flows and stock market development, its estimations, and the possible alternative estimation methods for generating the dynamic impact of shocks to the foreign portfolio equity flows on stock market capitalisation that includes Bayesian techniques. Lastly, literature on structural breaks is also covered, with specific focus on their likely implications on policy.

2.2. Efficacy of Capital Control and Liberalisation, and Policy Debate

Since the 2007 Sub-Prime Crisis and its eventual culmination in the global financial crisis (GFC) of 2008/09, calls for the reintroduction of capital controls have become rife (Huang and You, 2019; Zeev, 2017; Li and Rajan, 2015; and Grabel, 2015). The International Monetary Fund is now also less inclined to reject capital controls, arguing that they may be appropriate under certain circumstances (Sengupta and Gupta, 2019; Grabel, 2015; IMF, 2012; and Ostry et al., 2011). However, there is a dichotomy of views, with no consensus on the efficacy and desirability of greater capital controls versus capital account liberalisation[13] (also referred to as capital flow liberalisation, see Sengupta and Gupta, 2019; and IMF, 2012) with regard to foreign capital flows. This debate is prominent in literature (Guichard, 2017).

[13] Capital flows/account liberalisation aims at removing measures that limit the volume of capital flows (IMF, 2012).

These divergent views could partly be due to the benefits and also the risks posed to recipient countries by these flows (Koepke, 2019). In addition, the lack of consensus on how to best deal with foreign capital flows may be due to a lack of insight into the underlying process of the individual class of flows, which has a bearing on whether the effect of the flows will be persistent or short-lived. The former relates to the long-range dependence[14] these flows may be associated with, especially given that economics and financial data have been found to have long memory processes[15]. Such processes have correlations between values that slowly decay to zero, and implies that current values tend to have high dependence on past values (Tarasov and Tarasova, 2018). This dynamic memory in economic processes arises from economic agents incorporating past events into their decisions (Tarasova and Tarasov, 2018).

However, high volatility and precipitous increases associated with foreign capital flows, as noted by Sengupta and Gupta (2019), for example, as well as their tendency to stop suddenly, have resulted in calls for the use of capital controls as means of regulating these flows (Devereux, Young, and Yu, 2019). Proponents of capital controls contend that some measures of control on capital flows have tended to negatively affect the volatility of these foreign flows as they have acted like shock absorbers, or have indeed reduced their volumes, although at a cost of reduced flows for some class of foreign portfolio flows (Pasricha et al, 2018; Zeev, 2017; Li and Rajan, 2015 [16]; and Campion and Neumann, 2004). Possibly, an understanding of the intrinsic behaviour of these flows in terms of their underlying process, as for example suggested by Forbes and Warnock (2012)[17],

[14] Also referred to as long-range persistence or short/long memory. For example, see papers by Ergemen (2019); Benbassat et al. (2017); Fernandez (2011); and Breidt et al. (1998), for the interchange of these concepts, but essentially referring to the same thing.

[15] See, for example, Mensi, Tiwari and Al-Yahyaee (2019), Zheng, Liu and Li (2018), Tarasova and Tarasov (2018), Tarasov and Tarasova (2018), Ngene, Tah and Darrat (2017), Tarasov and Tarasova (2016), Škare and Stjepanović (2013), and Baillie (1996).

[16] However, controls on equity inflows were found to have no apparent impact on their volatility. Further, the study found that inward controls on FPI or FDI inflows had no statistically significant impact on the volatility of any form of equity inflows. They also found strong evidence of controls on FPI outflows to moderate the volatility of FDI inflows.

[17] Note that their suggestion was specifically in the context of unobserved components.

could help rule out the decline in the capital flows as a factor behind the reduction in the observed volatility.

The highlighted studies, however, seem to suggest that capital controls are not universally effective, since they seem to be effective for some classes of foreign capital flows and not others. In addition, the studies gave no consideration to how the underlying process of these flows can affect their volatility, although the presence of long memory in the volatility process of financial variables has been, for example, established by Baillie et al. (2019) and Baillie and Wook (2019). This may perhaps be the reason why Bekaert and Harvey (1997), contrary to some empirical outcomes, could not find any evidence that financial liberalisation induces volatility in the flows to these markets, but instead found significant reductions in volatility of capital flows into emerging markets that have undertaken capital account liberalisation. Thus, some empirical works show that capital controls are not effective in stemming the volatility of capital flows (Fernández, Rebucci, and Uribe, 2015).

The argument in favour of capital controls has also been advanced from the perspective of welfare gains, but with no consideration of how long or short memory in the capital flow processes can influence outcomes in other variables, including those related to welfare (see, for example Furceri and Loungani, 2018; Bumann and Lensink, 2016; and Kitano, 2011). Nevertheless, Devereux, Young, and Yu (2019), motivated by the problem of the sudden stop of capital inflows and the escalated rise in the outflows during the global financial crisis, concluded that capital controls may be suboptimal.

This inconsistence in the results on the role of capital controls in welfare maximisation may require a standardised approach to measuring the impact of capital controls on capital flows, as opposed to treating them as though they are the same, since some are of a short-term nature, while others are long-term and serve different purposes in terms of economic interests. The treatment could be in terms of data type (i.e., portfolio equity flows distinguished from portfolio debt flows, bank flows, FDI etc.). The second standardisation approach could be in terms of data properties or classes, such as the underlying process characteristics. For example Forbes and Warnock (2012), identified the need to consider unobservable components in foreign capital flows and this may be a non-trivial issue. The third standardisation approach could be on the methodology, especially if the data's underlying process has characteristics of long-range dependence. Classical statistical tools may therefore not be suitable for estimations or analysis of variables with such data, and may require other tools suitable for data with long memory (Tarasov and Tarasova, 2018).

Further, the debate in favour of the use of capital controls also arises from empirical findings showing that prior to the GFC, capital controls helped reduce vulnerabilities for the countries that implemented such measures (Ostry et al., 2011). The proponents of capital account controls have argued, for example, that these measures are necessary to prevent a build-up of financial sector imbalances, whose risks can be destructive to domestic financial markets (Guichard, 2017). Some proponents of capital controls have often made a case in favour of their implementation by citing Chile's capital control actions on inflows and outflows in the 1990's as having been macro-economically successful (Magud, Reinhart, and Rogoff, 2018; and Edwards and Rigobon, 2009), and citing the success of Malaysia's capital control actions that eventually appeared to have reduced the outflows (Magud, Reinhart, and Rogoff, 2018). However, with regard to the effectiveness of the controls in Chile, empiricists have questioned this interpretation, contending that its success had nothing to do with capital controls but more with favourable external conditions that included favourable terms of trade (Edwards and Rigobon, 2009).

Brazil has also been cited as a case where the imposition of capital controls has yielded desirable results (Chamon and Garcia, 2016). Despite the claimed Brazilian success story with capital controls, the assessment by Chamon and Garcia (2016) shows that the initial measures taken by Brazil after the global financial crisis were virtually ineffective in delivering the required results. It is claimed that a strong response by the authorities afterwards, which may have been a reflection of a combined effect of past actions, achieved the intended purpose. Nonetheless, this was at the expense of slowing down the Brazilian economy, owing to low inflow of foreign capital in the aftermath of the GFC, given the low domestic savings in Brazil (Chamon and Garcia, 2016).

Based on recent empirical evidence, capital controls have generally been found to be ineffective, and includes their failure to reduce volatility, as established by Fernández, Rebucci, and Uribe (2015). Thus, Jongwanich (2019) contends that placing controls on one type of flows to influence its direction may cause the other types of flows to move in an undesirable direction, thereby making the actions ineffective. Further, Boero, Mandalinci and Taylor (2019) empirically show that capital controls only deliver on their intended purpose in the short run and for some countries only, concluding that they are ineffective in the long-run. Similar views are held by Sengupta and Gupta (2019); Magud, Reinhart, and Rogoff (2018)[18]; Pasricha, *et al.* (2018); Li and Rajan (2015); and Forbes et al. (2015).

On the policy stance related to financial liberalisation, supporters of capital account liberalisation are of the view that this is necessary because free movement of capital has delivered benefits, such as financial deepening or financial sector development, welfare-enhancing funding of the current account imbalances, and promoting cross border risk sharing through portfolio diversification, to the associated countries (IMF, 2012). Further, they argue that liberalisation of capital accounts is necessary to avoid misallocation of local and global resources (Eichengreen, 2001a). Importantly, this strand of literature similarly does not address the role of long-range dependence in the behaviour of these flows, and its possible impact on the success or failure of capital flow management tools in the context of liberalised foreign capital flow policies. This is relevant as the interaction between economic variables are influenced by the memory function that connects them (Tarasov and Tarasova, 2018), and, as a system, these variables are affected by both the outcomes of other variables and feedback mechanisms (Schasfoort, 2017).

A further argument in support of capital account liberalisation is that risk premiums on financial debt issuance is reduced in countries with no capital controls, particularly for those countries with less developed domestic financial markets who, after undertaking financial liberalisation or openness, experienced favourable credit ratings for both sovereign and corporate issues. This, in turn, reduced their risk premiums with attendant reductions in their cost of capital (Andreasen and Valenzuela, 2016; Vithessonthi and

[18] However, Magud, Reinhart and Rogoff (2018) found that under country-specific circumstances capital controls could achieve their intended purposes, but does not do so as a generalised outcome.

Tongurai, 2012; Henry, 2003; and Alfaro, Chari and Kanczuk, 2017). These findings render support for the need to undertake financial liberalisation, as opposed to instituting capital controls in an economy. However, there is a possibility that the outcomes on the cost of capital may have coincided with the nature of the phase of the underlying process in the data that favours such an outcome at that specific time.

A further argument in favour of capital account liberalisation is the observed link between financial openness and capital gains for equities, and reduced volatility in exchange rates (Pasricha et al., 2018; Vithessonthi and Tongurai, 2012; Edwards and Rigobon, 2009; and Chari et al., 2004). Specifically, Vithessonthi and Tongurai (2012) established an increase in stock prices for firms in Thailand in the period in which capital account control measures were relaxed, although this price appreciation varied across sectors. Similarly, Chari *et al.* (2004), using firm level data from eleven Asian and Latin American emerging market economies, empirically found asset price appreciation for the stocks in which foreign investors invested after capital account liberalisation in the respective countries. In addition to its favourable effect on stock prices, Pasricha *et al.* (2018) also found that the easing of capital control restrictions lowered exchange rate volatility for sixteen emerging market economies, whilst Edwards and Rigobon (2009), in a study focused on capital controls and inflows into Chile, found that controls could however lead to greater exchange rate volatility.

Proponents of capital account liberalisation have also argued that foreign capital flow risks can be successfully managed using other capital flow management techniques that are not related to capital controls, such as macro-prudential measures. For example, Forbes et al. (2015), in a study based on international transaction data covering 2009 to 2011, found that macroprudential interventions slowed down foreign flows in 60 countries, whilst Pradhan et al. (2011) found macroprudential policy tools to be effective in curbing the inflows to a number of Asian countries.

Macroprudential actions are intended to deal with the externalities and market failures that may arise from the process of financial intermediation and activities of financial markets that could lead to the procyclicality of financial indicators/variables, and the resultant build-up in systemic risks (Cerutti, Claessens, and Laeven, 2017). Thus, macroprudential policies focus on reducing systemic risks that emanate from excessive financial procyclicality and from linkages with real and external factors (Bruno et al., 2017)[19].

In view of this, Neanidis (2019) tested the effectiveness of prudential regulation in safeguarding economic growth and financial stability within the growth framework in light of volatile financial flows[20]. Using a sample of developed, middle-income, and least developed countries, he found that bank regulatory policies tend to offset the undesirable effects of volatile capital flows on growth. Neanidis (2019)also established that countries which are relatively open with deep financial systems and exposed to macroeconomic volatility, tended to experience lower marginal gains, although they also experienced benefits from regulatory interventions. This study therefore concluded that regulatory interventions on foreign capital flows are effective in limiting financial system vulnerabilities. Further to this, Bergant et al. (2020) also showed that macroprudential regulation significantly moderate the impact of capital flow shocks induced by global financial shocks on emerging markets. Thus, macroprudential tools, such as those targeting bank capital and liquidity, as well as foreign currency mismatches and risky forms of credit, were found to be particularly effective compared to stricter capital controls. This finding was echoed by an analogous study dealing with inflows to India (Hiremath and Kattuman, 2017). Similarly, Zhang and Zoli (2016) also found macroprudential tools to be effective in dealing with the undesirable effects of foreign capital flows within a comprehensive sample of advanced and developing economies from across the world. Macroprudential policies that were found to have worked in dealing with equity flows, housing price growth, credit growth, and bank leverage (the very concerns associated with foreign capital flows), include loan-to-value ratio caps, housing tax measures, and foreign currency-related measures.

Of all the macroprudential measures, those related to reserve requirements and foreign exchange measures were generally found to be most applicable to foreign capital flows,

[19] Bruno, Shim and Shin (2017); and Gadanecz and Jayaram (2016) provide a comprehensive framework of macroprudential tools and their respective areas of focus as a guide to help deal with financial procyclicality and systemic risks, including those that may arise from foreign capital flows.

[20] This author provides a useful list of recent studies that focus on the effectiveness of macroprudential and banking regulatory policies in dealing with foreign capital flows with measures of success.

including foreign portfolio equity flows. Thus, Aysan, Fendoğlu, and Kilinc (2015), in a panel study of 46 countries (but mainly focussed on Turkey), found that macroprudential measures, including those related to foreign exchange supply and reserve requirements, assisted in making capital flows to Turkey less sensitive to global factors when compared to other countries. Similar findings were also reported by Zhang and Zoli (2016) for fourteen Asian countries, and by Brei and Moreno (2019) in a study considering an increase in reserve requirements for 97 Latin American banks across five Latin America countries.

However, despite the above evidence, care should be taken when considering macroprudential policy measures, as some of them are seemingly not different from capital control measures, such as the foreign exchange related measures (see for example Zhang and Zoli, 2016).

The ongoing debate between the proponents of capital controls and those of liberalisation suggests that the question of long or time dependence (long or short memory or long or short-range dependence) in capital flows may not be trivial. The implication is that capital flows may or may not respond to capital control intervention as expected, simply because of the nature of the underlying process at play during a particular time. Bruno et al.'s (2017) observation that increases in some classes of capital flows are followed by self-induced declines, suggests that the question of long-range dependence could be critical in highlighting whether capital controls are relevant for a given class of capital flows during a given period. Thus, the unobservable components of these flows need to be taken into account, as for instance suggested by Forbes and Warnock (2012).

However, on both sides of the policy debate there is seemingly little or no reference to the role of the underlying capital flow process that potentially causes their effect to be either persistent or transitory in a given economy, which in turn may assist in understanding whether capital controls or macro-prudential management approaches associated with financial liberalisation is optimal. For example, Sarno, Tsiakas and Ulloa (2016) supports the IMF's new position on capital controls stemming from their empirical findings that the "push factors" account for 80 percent of capital flows, but do not consider whether the shocks to these foreign capital flows have a persistent or an anti-persistent effect on them.

It is worth noting, however, that a small number of studies, including those of Hiremath and Kattuman (2017) and Cai, Dang and Lai (2016), have considered the underlying process of foreign capital flows in the context of its policy implications. The former study used a fractionally[21] integrated GARCH (FIGARCH) model to generate conditional volatility values of capital flows in the Indian stock market. The finding was that foreign institutional investors' (FII) flows have some limited influence on the Indian stock market volatility. The latter study used state space methods on foreign capital flows to China, finding gross equity inflows and gross bond flows to be anti-persistent. Both studies thus concluded that capital controls are not ideal in dealing with these flows, and therefore tilted towards supporting financial market liberalisation. These two studies are good examples of how information on the underlying process of foreign capital flows can contribute to the debate on the optimal policies for managing foreign capital flows.

2.3. Theoretical and Empirical Literature on Capital Flows

As previously indicated, capital flows have been extensively studied in both theoretical and empirical literature, but with little reference to their underlying process. Further, policies on the control or management of foreign capital flows rely on this incomplete research, whereas Hiremath and Kattuman (2017), for example, have shown that greater insight on the underlying process of foreign capital flows may lead to improved policy conclusions in this regard.

2.3.1 Capital Flows Theoretical Literature

The theoretical literature on capital flows (including portfolio equity flows) has largely focused on explaining the determinants of capital flows, rather than the role of the underlying process. One such theory is the *Neoclassical Theory of Capital Flows*, which suggests that capital will flow from countries with lower returns to countries with higher returns, and also from countries with high income to those with low income (Alfaro *et al.,* 2008). The theory is not specific on the type of capital (*i.e.,* FDI, FPI or bank flows) but its

[21] Variables with long memory or long-range dependence are said to be fractionally integrated, as opposed to being of integer order of integration (Baillie, 1996).

importance is the postulation that investors will move their funds across borders in pursuit of private interests to achieve favourable returns.

However, this theory is disputed by Lucas (1990), who questions the validity of this proposition under what has come to be known as the Lucas Paradox. Besides Lucas (1990), there is a proliferation of literature criticising the theory under the theme of "puzzles". which includes the Feldstein–Horioka Puzzle (Feldstein and Horioka, 1980); the Home Bias Puzzle (Pesenti and van Wincoop, 1996), and the Allocation Puzzle (Gourinchas and Jeanne, 2013). The puzzles relate to inadequate (but perhaps to put it realistically, low) capital flows - particularly equity flows into international markets.

The Lucas Paradox contends that foreign capital flows predominantly move to relatively rich countries and has been supported for example by Aluko and Ibrahim (2019); Akhtaruzzaman, Hajzler, and Owen (2018); Mumtaz et al., (2014); and Obstfeld and Rogoff (2001). With regard to the Feldstein–Horioka puzzle, this is founded on an established high correlation between savings and investments in the OECD countries. Essentially, this correlation means that savings mobilised in the OECD countries have been channeled within such countries under different investment vehicles. The Home Bias Puzzle emphasises the observation that most investors in developed countries have the bulk of their investment in domestic markets. Nonetheless, there is debate on that factors causing local investors to favour domestic markets as opposed to going into international markets, as observed by Obstfeld and Rogoff (2001). Similarly, the Allocation Puzzle argues that developing countries are net exporters of capital, partly attributed to the accumulation of foreign reserves by their central banks, which are then mainly invested abroad (Gourinchas and Jeanne, 2013).

However, although Forbes and Warnock (2012) suggest that the unobservable components in capital flows data may have a bearing on the outcome, the Lucas Paradox and the Allocation Puzzle Hypothesis, and the other puzzle-related theories of capital flows' arguments ignore the role of persistent or anti-persistent behaviour in developing countries, who are net exporters of capital. In view of this, there appears to be a gap in the theory when it comes to the policy debate on the efficacy of capital controls or capital account liberalisation. The *Neoclassical Theory on Capital Flows,* the Lucas Paradox and the Allocation Puzzle Hypothesis, and those that are alike may be too general in not distinguishing between various classes of foreign capital flows and their possible underlying process.

Another theoretical proposition that has sought to explain the movement of foreign capital flows, specifically in the context of geographical diversification, is the *Portfolio Diversification Theory*, advanced by Markowitz (1952). This theory suggests that foreign capital flows are likely to move between two countries when their returns are negatively correlated. This means that an investor with assets spread between two or more countries may not be worse off on average as losses from one jurisdiction may be compensated for, or minimised, by gains from assets in another jurisdiction. Thus, according to French and Poterba (1991), the correlation of returns in different equity markets should be negative for capital flows to move from home to foreign markets. However, Portes and Rey (2005) have shown that geographical diversification is not generally significant in determining cross-border asset trades. These mixed results, which question the validity of the *Portfolio Diversification Theory*, again may be highlighting the need to understand the role and nature of the underlying process in the behaviour of foreign capital flows, which may flow to a particular country either consistently or at intervals.

Yet another theory on the determinants of capital flows is the *Flow Theory of Capital Movement,* credited to Sachs *et al*. (1996), which is based on the role of interest rate differentials between home and foreign markets. This theory states that a relative increase in the domestic interest rate will increase the inflow of foreign capital, and vice versa (see also Mercado, 2020; and Brooks *et al.*, 2004). The theory specifically explains the changes in a country's capital stock owing to changes in both domestic and foreign interest rates, alongside changes to other factors that are of non-interest rate in nature. The silence on the role of the long-range dependence of capital flows in this theoretical proposition and the ones stated above can be understood from the perspective that this phenomenon, which first entered the economics space through the works of Granger (1966) is data dependent. Although Granger (1966) cautioned that not every economic data set would include such a phenomenon, since then there has been a proliferation of studies on long memory in economics and finance generally[22].

Nonetheless, the usefulness of the flow theory of capital movement generally is its application in empirical work by Eniekezimene (2013), estimated using ordinary least squares methodology with an error correction model specification. Foreign portfolio investment was found to have a positive impact on capital market growth – market capitalisation was taken to be its proxy – with the speed of adjustment from short run to long run being relatively high by way of an absolute value of 66%, suggesting some mean reversion which could imply stationarity.

A further theory on foreign capital flows is the *Portfolio Rebalancing Hypothesis*. This theory postulates that investors reallocate funds away from assets in their portfolio that have appreciated in value (due to price rises and/or currency gains) towards those that have depreciated. In so doing, they aim at restoring the optimal portfolio balance. The main objective of a portfolio rebalancing is to minimise risk relative to a target asset allocation, rather than to maximise returns. The issue in portfolio rebalancing is that as a portfolio's investments produce different returns, the portfolio will likely drift from its target asset allocation and thereby acquire risk-and return features that may be inconsistent with an investor's goals and preferences. Given this outcome, portfolio rebalancing will help investors to maintain their target asset allocation and avoid a "portfolio drift" phenomenon.

Hau and Rey (2004) empirically explore whether the international data on equity market returns, equity portfolio flows and exchange rate returns are consistent with portfolio rebalancing with regard to foreign equity flows by global investors' transactions. Their findings confirm that global investors tend to move funds across borders to minimise risks (especially foreign exchange risk) as they seek equity returns. Curcuru et al.(2011) use portfolio-based data and techniques and find that U.S. investors are engaged in trading behaviour that suggests rebalancing of their international portfolios, as they do not chase past returns. These two empirical works do not consider issues of long-range

[22] See, for example, Mensi, Tiwari and Al-Yahyaee (2019); Tarasov and Tarasova (2018); Wenger, Leschinski and Sibbertsen (2018); Ngene, Tah and Darrat (2017); Sensoy and Tabak (2015); Cajueiro and Tabak (2010); Couillard and Davison (2005); and Baillie (1996).

in assessing the validity of the portfolio rebalancing theory given that the issue of persistence or short memory could be an influencing factor.

Regarding a theoretical relationship between foreign capital flows, particularly foreign portfolio equity flows, and stock market capitalisation, and therefore how these flows affect stock market development, there seem to be no formal theory available in literature on the matter. However, in an extended *Calderon-Rossell* framework (originally developed by Calderon-Rossell, 1991 and 1990), a theoretical proposition explaining stock market development using stock market capitalisation as a proxy, foreign capital flows variable is incorporated as one of the determinants of stock markets development only in an empirical set up. Nonetheless, the author could not find any formal theory in the literature to explain the interaction between foreign capital flows and stock market capitalisation to support this empirical strategy, either in terms of gross inflows or gross outflows or, indeed, in the context of the relationship between net flows and stock market capitalisation.

2.3.2. Capital Flows Empirical Literature

Like the theoretical literature, empirical research on foreign capital flows (including foreign portfolio flows) focuses largely on their determinants, destabilising impact on macroeconomic indicators, and volatility, without much consideration of their long-range dependence, and thus their underlying process and its implications on policy.

2.3.2.1. Determinants of Capital Flows and Long-Range Dependence

Determinants of capital flows have been widely studied[23] using methods such as fixed and random effect panel techniques, panel GMM, Bayesian dynamic latent factor modelling, principal component analysis, Autoregressive Distributed Lag (ARDL), structural VAR and Granger causality, among other methods[24]. However, the type of estimation methods

[23] Empirically, determinants of capital flows are generally found to include both country specific factors (e.g. financial openness, institutions, and human capital), as well as "pull" factors (domestic fundamentals making recipient countries attractive) and "push" factors (unfavourable conditions in countries of origin). Other factors include trade in financial services, domestic credit ratings, black market exchange rate premiums, interest rates, and real economic activity.

[24] See, for example, Davis et al. (2019), Asiamah et al. (2019), Grigorian (2019), Lafuerza and Servén (2019), Wah Hlaing and Kakinaka (2019), Singhania and Saini (2018), Vo (2018), Kumar (2018), Byrne and Fiess (2016), Sarno et al.(2016), Garg and Dua (2014), Forbes and Warnock (2012), De Santis and Lührman,

generally used in this strand of literature usually does not consider the long-range dependence in the data series. For panel estimation methods, for example, this could be because panel estimation procedures applicable to data with fractional integration features, one of the attributes of long-range dependence, only appeared in the literature very recently. The fractionally integrated panel data modelling of individual and interactive fixed effects facilitates contemporaneous correlations between the innovations of the panel-dependent variable and the covariates to achieve estimations, including generally the integration of time varying features, trends and capturing of long range dependence features (see for example Ergemen, 2019; Robinson and Velasco, 2018; Ergemen and Velasco, 2017; Phillips and Lee, 2016; and Robinson and Velasco, 2015).

Surprisingly, although the use of fractional cointegration in empirical works within finance and economics now abounds using VAR models for fractional processes (see Salisu *et al*., 2019; and Johansen and Niels, 2012 for examples), the long history of estimating fractional cointegration in literature[25] has not stimulated much research interest in foreign capital flows using this approach. However, as this method involves testing for long memory effects prior to investigating the presence of fractional cointegration, when applied to capital flows, it should shed light on their underlying process. The presence of long memory of fractional order and fractional cointegration has, for example, been found in stocks in Islamic countries by Salisu *et al*. (2019) - an indication that ignoring fractional integration properties when modelling long run economic behaviour may lead to wrong conclusions. This may also be true of foreign capital flows, including foreign portfolio equity inflows and outflows.

Similarly, applying Granger causality to data that has long memory, as developed by Chen (2006), also does not appear to have been utilised in analysing capital flows. This could be due to this method appearing in literature only after, for example, Mukherjee *et al.* (2002)'s work on capital flows, which used the classical Granger causality method that does consider long-dependence properties in the data set used. The relatively recency of

(2009), Portes and Rey (2005), Mukherjee, Bose, and Coondoo (2002), Fedderke and Liu (2002), Kono and Schuknecht (1998), Taylor and Sarno (1997), and Fernandez-Arias (1996).

[25] See, for example, Caporale and Gil-Alana (2014), Davidson (2005), and Baillie and Bollerslev (1994).

the methods used in estimating variables with long memory in a bivariate and multivariate setup may be the reason why even recent empirical studies on the determinants of foreign capital flows, such as those by Singhania and Saini (2018), Kumar (2018), and Byrne and Fiess (2016), are silent on the issue of long-range dependence in these flows. Therefore, with the availability of tools to deal with data that is of fractional order of integration in economic and financial data, there appears to be an opportunity to extend their use more widely to foreign capital flows data in the context of bivariate or multivariate analysis. This may be helpful in informing policy options related to their control and management, as for example demonstrated by Hiremath and Kattuman (2017).

Two papers on the determinants of foreign capital flows that are worth mentioning in the context of this study, even though it is not addressing capital flow determinants, are those by De Vita and Kyaw (2008) and Culha (2006). Although neither considered issues of long-range dependence, these two papers both recognise the importance of establishing the dynamic effect of shocks to capital flow determinants on the levels of foreign capital flows over time. The authors in this regard highlight the role of impulse response functions (IRFs) on establishing and communicating the behaviour of foreign capital flows over time using structural VAR estimation procedures.

The issue of incorporating IRFs is in line with the present study, which seeks to establish the dynamic behaviour of market capitalisation when hit by shocks to foreign portfolio equity flows. As observed by De Vita and Kyaw (2008), it is possible that the relative significance of estimated coefficients of the determinants of foreign capital flows may vary across time horizons. There is therefore a need for the estimation of impulse responses to trace the effect of shocks propagation over time, and this may also be appropriate in the case of the determinants of stock market capitalisation especially for foreign portfolio equity flows as in the context of this study.

In summary, however, literature on the determinants of capital flows indicate that both pull factors, such as better economic performance, a sound general government primary balance, a greater degree of trade and financial account openness and stable exchange rate (Calderón and Kubota, 2018), and push factors, can be key determinants of capital inflows.

2.3.2.2. Capital Flow Volatility and Long-Range Dependence

A second focus area of the empirical foreign capital flow literature is the determinants of flow volatility, but again only a few studies consider the role of long-range dependence in the volatility of foreign capital flows. A key contribution to the literature on the subject of capital flow volatility is Claessens et al. (1995)'s paper with an argument that both short and long term capital flows are prone to volatility. Subsequently, Calvo and Mendoza (2000) has attempted to explain the problem in a theoretical setup within the context of portfolio rebalancing.

A number of other factors have generally been identified as contributing to capital flow volatility. For example, Opperman et al. (2017), employing a panel estimation procedure for sub-Saharan African data for the period 1990 to 2016, established that global liquidity accounted for the increase in portfolio equity volatility. However, economic growth, as well as the quality of macroeconomic policies, were found to be significant pull factors that decrease the volatility of foreign portfolio equity flows. Pull factors were also confirmed to be vital determinants of equity flow volatility, as found by Pagliari and Hannan (2017), based on a panel study using quarterly data of 65 countries over the period 1970 to 2016. However, Forbes and Warnock (2012) found global (push) factors, particularly global risk, as key in explaining the volatility of flows. Thus, these authors identified an increase in global risk to be associated with sudden stops in capital flows by foreign investors, and a reduction in capital flows by domestic investors. Specifically, the decrease in global risk was found to be linked to surges in capital flows.

Empirical results generally indicate that both short and long-term capital flows are predisposed to volatility, which is largely induced by information asymmetry among investors (Bacchetta and van Wincoop,1998). Financial liberalisation was also identified as a factor with a bearing on capital flow volatility (Kono and Schuknecht,1998), although this contrasts with the findings of Fernández, Rebucci, and Uribe (2015) and Bekaert and Harvey (1997). Kono and Schuknecht (1998) argued that liberalisation of financial services trade, with its attendant diversity of instruments, attracts foreign financial institutions, which in turn leads to less distorted and less volatile capital flows. This could be due to the offsetting behaviour of the volatility of individual elements in the capital account, as found by Becker and Noone (2009). In SSA specifically, global liquidity has been found to have mixed effects on capital flow volatility – whereas it contributes to reducing only FDI volatility, it seems to be contributing to portfolio equity flow volatility (Opperman et al., 2017).

Additionally, the normalisation of monetary policy following the unconventional monetary policy (UMP) (involving forward guidance on the future path of interest rates, and bond purchases referred to as quantitative easing, QE) pursued by the US Federal Reserve Bank (FRB) in the wake of the 2008-2009 global financial crisis, is among the factors found to have induced the volatility of capital flows. Anaya et al.(2017) identifies portfolio flows as the main channel through which FRB's UMP impulses were transmitted to the emerging markets, leading to the surge in the inflows in these markets. However, the normalisation of monetary policy led to the reverse in the flows (i.e. causing a net outflow) in emerging markets, thereby causing volatility in portfolio flows. This was particularly true at the time of the decision in 2013, which has come to be known as the taper tantrum in literature, and at the actual implementation of monetary policy normalisation in late 2015 (Acharya and Krishnamurthy, 2018). The decision to taper with QE in 2013 indeed created some volatility, with emerging and frontier market inflows slowing down, and outflows increasing under the *flight to safety* principle (Dahlhaus and Vasishtha, 2014).

This strand of literature further confirms that capital flow volatility is a concern for macroeconomic and financial stability,[26] given that capital flows are indeed volatile (Bluedorn et al., 2013 and Levchenko and Mauro, 2007). Further, although Bluedorn et al. (2013) contends that these flows are now virtually the same in behaviour across countries and relatively less volatile than before, earlier studies found greater volatility for emerging market and developing economies (see, for example, Levchenko and Mauro, 2007; and Broner and Rigobon, 2006).

To conclude this section, it is notable that the vast majority of studies do not recognise the role of the underlying process in shaping the volatility behaviour of foreign capital

[26] See, for example, Acharya and Krishnamurthy (2018), Anaya et al. (2017), Opperman et al. (2017), Pagliari and Hanna (2017), Dahlhaus and Vasishtha (2014), Bluedorn et al. (2013), and Forbes and Warnock (2012).

flows[27]. Further, with the notable exception of a study by Hiremath and Kattuman (2017), this strand of literature ignores how the underlying process of these flows, in the context of long or short memory, impacts on their ongoing volatility – information that could lead to insights on whether less or more capital controls best deals with flow volatility.

2.3.2.3. The Underlying Process of Capital Flows: Long-Range Dependence

The few prior studies that have considered the underlying process of capital flows have used one of three different methods to estimate aspects of long-range dependence on some classes of foreign capital flows. The first of these is the variance ratio of the state and measurement equations estimated with a state space approach via the Kalman filter, and involves estimating the variances of the state and measurement equations (see Sarno and Taylor, 1999a and 1999b and Cai, Dang and Lai, 2016). The objective of these studies was to establish the underlying process of portfolio equity flows (EF), portfolio bond flows (BF), official flows (OF), commercial bank credit (BC), and foreign direct investment (FDI) for Asian and Latin American developing countries. The former three were found to be non-persistent and mostly transitory in nature, implying that they were more likely to be anti-persistent in behaviour. For Australia and Japan, however, equity flows were found to be persistent, as data for the two was dominated by the permanent component.

These mixed results suggest that portfolio equity flows may be characterised by persistent behaviour in more advanced economies, but anti-persistence in developing countries. The latter finding resulted in policy advice against capital controls, but despite this, some countries covered by these studies, such as Chile, Brazil and Indonesia, experimented with capital controls following undesirable capital flow behaviour in the wake of the liberalisation of their financial markets (Sengupta and Gupta, 2019). However, as the above research excluded African countries, there remains a lack of knowledge on the underlying process of capital flows for sub-Saharan Africa countries.

The variance ratio, which utilises the methods devised by Lo and Mackinlay (1988), involving the ratio of the same series' variances in which one has its variance adjusted of heteroscedasticity, is also used (but not estimated) in the state space setup. Hiremath and

[27] The few exceptions to this include the studies by Ning et al. (2017); Bluedorn et al. (2013); Forbes and Warnock (2012); Cai, Dang and Lai (2016); Levchenko and Mauro (2007); Becker and Noone (2009); Broner and Rigobon (2006); and Sarno and Taylor (1999a).

Kattuman (2017), for example, utilised this approach and estimated persistence in the FII flows to India using daily data. Based on this variance ratio, they found some evidence of persistence in the flows to India throughout the period, but differing in intensity at different times, and thus described it as time varying. This outcome suggests that flows to India never assumed an anti-persistent behaviour, nor were they a random walk. However, these results differ from those of Sarno and Taylor (1999a), Sarno and Taylor (1999b) and Cai, Dang and Lai (2016) on developing countries, as indicated above. This may be due to the difference in the period covered, as well as the frequency of the data, and perhaps also due to the different estimation methods. However, in a similar study employing the variance ratio in a non-state space approach for developed and emerging market countries using daily data, Froot *et al.* (2001) found the underlying process for both foreign portfolio equity inflows and outflows to be highly persistent, consistent with the findings of Hiremath and Kattuman (2017). These authors described the persistence as being of the type where, for instance, a shock to the inflows today will be associated with slightly greater inflows over a relatively long subsequent period of time.

As with the previous strand of literature, policy prescriptions on dealing with foreign capital flows also followed from empirical findings on long range dependence obtained using the above method. Thus, Hiremath and Kattuman (2017), whose study established that foreign institutional investor flows to India are markedly persistent at certain times, and therefore may not be destructive to its market, recommended that the Indian authorities should continue pursuing gradual capital account liberalisation as opposed to doing it swiftly. In view of the flows being persistent, the policy recommendation of maintaining some measure of capital controls is intuitive in the sense that if there was a shock to the inflows that results into an adverse effect to either macroeconomic or financial variables, the impact will also likely be persistent. Having some measure of capital controls in this situation can help address the problem of a persistent adverse impact by limiting the inflows in one way using some capital control instrument(s).

The second methodology found in the literature for measuring persistence or anti-persistence in capital flows, and thus long-range or short-range dependence, is based on autoregressive and autocorrelation coefficients. Time series data with long-range dependency properties exhibit slowly decaying Autocorrelation Functions (ACF), a sign of persistence, and it is argued that economic time series data also has long-range dependency (Campbell et al., 2007). Long-range dependency implies that observations in the remote past are non-trivially correlated with their distant future counterparts, according to Campbell et al. (2007). Bluedorn et al. (2013), Becker and Noone (2009), and Levchenko and Mauro (2007) all employed ACF in understanding the behaviour of capital flows. This stream of literature generally finds particularly gross foreign portfolio equity flows to be anti-persistent for both developed and developing countries. Nonetheless, this information has not been documented in terms of its utilisation in guiding policy on foreign capital flows management.

The third strand of literature on the underlying process of capital flows deals with fractal analysis and its estimation of the Hurst parameter[28]. Unlike the other methods above, this technique belongs to the non-linear methods for time series data (Papaioannou et al., 2019), and is non-parametric. Therefore, it may be suitable for dealing with data that may have fat tails (i.e., data that may not be symmetrically distributed). The methodology is credited to Hurst (1951), and popularised by Mandelbrot and Wallis (1968). Studies on the use of fractal analysis on capital flows seem to be scant. However, a study by Ning et al*.* (2017) does use multifractal analysis to investigate long-range dependence in short-term international capital flows for China, via a multifractal detrended fluctuation analysis (MF-DFA)[29] method to estimate the multifractal generalised Hurst exponent. The results of the study confirm the presence of multifractals in the series, an indication that short-term foreign capital flows in China is non-linear, and more importantly, exhibit long range dependence. The multifractal nature of the short-term capital flows is attributed to long range correlations (tendency of volatility clustering) in the data, which is also found to have fat tails. The researchers concluded that, since capital flows associated with China are non-linear with two factors driving the observed multi-fractal behaviour, non-linear methods may be appropriate to use when analysing China's capital flows.

[28] This is interchangeably used with the words Hurst coefficient or Hurst exponent.

[29] The DFA has generally been employed when establishing long-range power-law correlations in seemingly non-stationary series although users have not taken into account the order of integration which is critical as for example established by (Fernandez, 2011).

The case for the Hurst parameter estimation of capital flows can therefore be made based on the non-linearity of China's capital flows as established by Ning *et al.* (2017), and the general conclusion that economic and financial variables may have long memory (see for example Nguyen et al., 2019, and various other studies[30]).

However, even if Ning et al*.* (2017) estimated long-range dependence in foreign capital flows, the results from this study are not linked to any policy prescription related to capital flow management.

2.4. Long-Range Dependence Estimations: The Hurst Statistic

Long-range dependency estimated through fractal analysis and its representative Hurst statistic has a wide application in economics and finance (Nguyen *et al.*, 2019). Any statistical inference that ignores this may result in such inferences being totally invalidated (Beran, 1992). It is therefore surprising that it has had a little application in empirical literature on foreign capital flows. The estimation of the Hurst parameter has, amongst other reasons, been done to determine long memory volatility and stochastic volatility persistence in stock market returns, as well as factor portfolio returns in American, European and some sub-Saharan African markets.[31] Thus, estimated Hurst coefficients have been used to establish the dynamic efficiency (based on long range properties) of stock markets across various countries, with results suggesting changes in the level of stock market efficiency at different times under different circumstances[32].

In addition to market and asset prices returns (including their volatility) and market efficiency, fractal analysis in estimating the Hurst coefficient has also been applied to assess carry trades returns, performance assessment of hedge funds, establish monetary policy stances through interest rates dynamics, and as a useful tool in developing financial market trading strategies, thereby signifying its wider use[33]. However, although

---

[30] Including the works of Mensi, Tiwari and Al-Yahyaee (2019), Wenger Leschinski and Sibbertsen (2018), Tarasova and Tarasov (2018), Ngene, Tah and Darrat (2017), Tarasov and Tarasova (2016), Sensoy and Tabak (2015), Cajueiro and Tabak (2010), Couillard and Davison (2005), and Baillie (1996).

[31] See, for example, Nguyen et al. (2019), Auer (2018), Dima and Dima (2017), Martinez et al. (2016), Gyamfi et al. (2016), Chimanga and Mlambo (2014), and Musongole (2002).

[32] See for example, Hiremath and Kattuman (2017), Sensoy and Tabak (2016), Sensoy and Tabak (2015), and Sensoy (2013).

[33] See, for example, Flint and Maré (2017), Auer and Hoffmann (2016), Auer (2016a), and Auer (2016b).

the Hurst parameter estimation has been undertaken on a relatively wide set of financial variables, its application to foreign capital flows has been minimal, as stated earlier.

There are several methods used in estimating the Hurst coefficient and, as pointed out by Cajueiro *et al.* (2009), computing the Hurst exponent is a challenging task. Many techniques are used in estimating the Hurst exponent, in some cases resulting in the use of different tools, leading to different Hurst parameter estimates for the same set of data. In this regard, Serinaldi (2010) provides empirical guidance on the choice of Hurst exponent computing method, so as to avoid calculating a spurious Hurst parameter with whatever technique is used. This guidance is rooted in the understanding that it is possible to obtain the same Hurst parameter estimate or value for two different sets of data with, respectively, underlying processes of either fractional Brownian motion (fBm), or fractional Gaussian noise (fGn), despite the two sets of data having different underlying processes (Eke et al., 2002). The fGn is the first difference of the fBm, which is a fractional differentiation of the Brownian motion or random walk (Delignieres and Torre, 2009). The fBm and the fGn have different statistical properties in terms of issues of stationarity, with the fBm having stationary increments (Delignieres et al., 2006)[34].

Cannon et al. (1997) showed that there is a unique Hurst exponent which characterises both the fBm and the fGn signals, and it is therefore necessary to understand whether specific data is of the fBm or fGn signal before undertaking an empirical analysis. Serinaldi (2010) argued that this can help with the use of appropriate estimation method(s) to avoid estimating an ambiguous Hurst exponent, specifically because some methods are suitable for the fGn-like signal, whilst others are ideal for the corresponding fBm signal. Thus, Serinaldi (2010) estimates of the Hurst coefficient on spot energy and commodities future prices, as well as stock market indices, yielded consistent results of the Hurst exponent for all the methods used when fractal signal classification (fBm or fGn) was taken into account.

However, the economics and financial literature indicate that it is common for researchers to conduct fractal analysis in computing the Hurst parameter without

[34] A detailed description of the two series can be found in the work of Mandelbrot and Van Ness (1968).

considering the fractal signal classification of the underlying data[35]. To avoid policy regrets arising from the empirical work with spurious Hurst estimates, it is important to undertake fractal signal classification as advised by Serinaldi (2010) and others like Eke et al. (2002) and Delignieres et al. (2006), regardless of the method used in estimating the Hurst parameter. Similar sentiments are advanced by Resta (2012), who identifies the need for a correct signal identification when estimating the Hurst parameter. Fractal signal classification has gained prominence in physiology[36] and electronic and communication engineering[37].

A number of studies have evaluated the efficacy of different methods for estimating the Hurst coefficient, with the pioneering works of Taqqu, Teverovsky, and Willinger (1995); and Montanari, Taqqu, and Teverovsky (1999), among others, providing insight on the choice of methods or ways of undertaking estimations on long-range dependence. Rea et al. (2013), who identified biasness in most of the estimators based on either the length or value of the Hurst parameter used in the simulations, found the Wavelet technique to be the most effective method. Similarly, Kirichenko et al. (2011) showed that the detrended fluctuation analysis (DFA) and wavelets methods had minimal bias for stationary series. However, the DFA was also accurate for non-stationary series, while the wavelet approach performed better in the presence of a slight trend in the data. Fernandez (2011) established that the periodogram, the Geweke and Porter-Hudak (GPH) method, the quasi-maximum likelihood (QML) and the modified R\S followed by the DFA, the modified DFA (MDFA), and the Centered Moving Average (CMA), all had a reasonable bias for the stationary series. However, the periodogram, GPH, QML, DFA, MDFA, and the CMA estimators were found to be unbiased for data which is fractionally integrated (i.e. data which is of non-integer order of integration). Chamoli et al.'s (2007) assessment show that the wavelet and the R\S methods yield consistent results regardless of data length.

[35] See for example, studies by Nguyen et al. (2019), Ning et al. (2017), Hiremath and Kattuman (2017), Gyamfi et al. (2016), Lahmiri (2015), Sensoy and Tabak (2015), and Kristoufek and Vosvrda (2013), among others.

[36] See, for example, Phinyomark, Larracy, and Scheme (2020), Nagy et. al. (2017), Schaefer et al. (2014), De La Fuente et al. (2006) and Eke et al. (2002).

[37] Examples include Balcerek & Burnecki (2020), Ying et al. (2011), Li, Zhao, and Chen (2010), and Li et al. (2009).

From these assessments, the DFA and the wavelet approach are generally found to be the best methods, as they result in minimal bias, in terms of both the underlying signal property of stationarity or non-stationarity, and the length of the data. Specifically, the wavelet method showed a minimal bias for stationary series, but was good for data with a slight trend, whereas DFA was accurate for all types of series that are fractionally integrated, regardless of length.

2.5. Foreign Portfolio Equity Flows and Stock Market Development

The results of empirical studies on the underlying process of foreign capital flows have not been widely utilised in the policy debate on the efficacy of capital controls and financial liberalisation. However, even this may not be sufficient to settle the policy debate, and particularly so for foreign portfolio equity flows. In this regard, understanding the impact of foreign portfolio equity flows on stock markets' development may be useful complementary information in the adoption of an optimal policy intervention on the foreign portfolio equity inflows and outflows. Specifically for sub-Saharan Africa and emerging stock markets, foreign portfolio equity inflows and outflows are important in augmenting stock markets' liquidity (Peranginangin et al., 2016; and Yartey and Adjasi, 2007) which, has a positive bearing on stock market capitalisation or development (Ho, 2019).

Some studies, such as those of Li et al*.* (2017) and Wang et al. (2016), have revealed how foreign portfolio equity flows contribute to the increase or decline in stock market capitalisation and other price sensitive stock market indicators. Both of these studies established the presence of a bi-directional relationship between foreign portfolio equity flows and stock prices for China, indicating that there are times when foreign inflows drive prices and other times when price movements induce inflows. Further, these flows were found to have a persistent effect on stock prices, increasing the risk that portfolio equity inflows induce stock price bubbles in the Chinese equity market. On the other hand, there is also some evidence of foreign portfolio equity flows having no influence on stock market return, and by implication stock prices, in China (Wei et al., 2018). Similar results, i.e. that foreign portfolio equity flows have no influence on stock market returns, were also found by Ndong (2015) and French (2011) for a number of African stock exchanges.

This may suggest that when stock price data is transformed into returns, some information that have an underlying correlation with foreign portfolio equity flows may be lost. This is possibly why Tillmann (2013), using panel VAR on five selected Asian countries that had relatively high levels of inflows, found a positive impact of capital flows shocks on stock prices (in levels), with a likely attendant positive impact on stock market capitalisation. Similarly for South Africa, a positive impact of foreign portfolio equity inflows on the All Share Index (ALSI) of the Johannesburg Stock Exchange (JSE) was found in both the short and long run based on the data that was in levels (Gossel and Biekpe, 2012). This renders support to the belief that data in levels may be more suitable than the transformed equivalent in establishing the relationship between foreign portfolio flows and stock market prices. The present study similarly envisages the use of data in levels so that there is no loss of information that may come with some types of transformations.

For studying the impact of various factors on stock market development, Garcia and Liu (1999) identified two approaches, namely institutional and macroeconomic. The former focuses on the role of factors such as property rights, clearance and settlement, transparency and inside information problems, taxation issues, other governance indicators and accounting standards, in influencing stock market capitalisation. The macroeconomic approach, on the other hand, investigates how income growth, savings and investment, financial development, inflation, and other macroeconomic variables influences market capitalisation. In addition to these factors, private capital flows, measured in terms of foreign direct investment and net private capital flows, both as percentages of GDP, has been included as an additional macroeconomic factor (for example see Yartey, 2008). Further, foreign portfolio investments (see el-Wassal, 2005) and exchange rate volatility (see, for example, Adebowale and Akosile, 2018; Adeniyi, 2017; Mlambo, *et al*., 2013; and Olugbenga, 2012) have also been studied as factors impacting stock markets' capitalisation and/or development.

The most popular theoretical framework for studying stock market development is the *Calderon-Rossell* partial equilibrium model,[38] credited to Calderón-Rossell (1991 and

[38] See, for example, Akileng et al. (2018), Sezgin and Atakan (2015), Kemboi and Tarus (2012), Yartey (2010), Yartey (2008), and el-Wassal (2005).

1990). In the *Calderon-Rossell* model, market capitalisation, the proxy for stock market development, is influenced by economic growth and stock market liquidity. However, from an empirical perspective, following on the approach of Garcia and Liu (1999), the *Calderon-Rossell* model has been estimated with the inclusion of other variables, such as foreign private capital flows[39].

In sub-Saharan Africa specifically, studies using the *Calderon-Rossell* model to establish factors affecting stock market capitalisation in Botswana, Ghana, Kenya, Nigeria, South Africa and Zimbabwe, found foreign portfolio investment to be positively and statistically significantly related to market capitalisation (el-Wassal, 2005; Yartey, 2008; and Yartey, 2010). The main limitation of these studies, however, is that they did not show how dynamically a shock on the foreign portfolio/capital flows impacts stock markets over time, specifically regarding magnitude and persistence (or lack thereof). Therefore, it is difficult to trace how a shock on foreign capital flows may influence sub-Saharan Africa stock markets' capitalisation, and thus the extent of their development. Addressing this gap in the literature requires the estimation of impulse response function to trace the effects or impact of shocks to foreign portfolio flows and their effect on sub-Saharan African stock markets.

In a departure from the use of the *Calderon-Rossell* model as the theoretical approach underpinning studies on stock market development, Nyaga (2017), Eniekezimene (2013), and Chukwuemeka et al. (2012) found a positive relationship between foreign portfolio equity flows and stock market capitalisation - in this case for Kenya and Nigeria. The positive relationship between portfolio inflows and stock market capitalisation of the Nairobi Securities Exchange (NSE), established by Nyaga (2017), agrees with the findings by Kemboi and Tarus (2012), although the model used in the former study was a simple regression estimated under the ordinary least square (OLS) method, with the data being in levels. Since the technique used did not account for issues of stationarity, the results reported should be taken with some reservations without knowledge about possible

[39] See, for example, studies by Sezgin and Atakan (2015), Kemboi and Tarus (2012), Yartey (2008), and el-Wassal (2005).

cointegration of the two variables used, namely foreign equity portfolio inflow into Kenya and NSE stock market capitalisation.

Once more none of the country specific studies presented above considered the dynamic role of shocks to foreign capital flows in influencing market capitalisation. It is worth exploring this aspect in addition to understanding the underlying process of foreign capital flows, if empirical work must contribute towards reaching a consensus on the issue of what would be the optimal balance between capital controls and financial liberalisation.

2.6. Estimating the Dynamic Impact of Shocks: Bayesian Techniques

The estimation of the *Calderon-Rossell* model and its modified version has largely involved the use of the OLS, VECM, ARDL, GMM, IV, and the panel regression estimation methods[40]. With a short data span that characterise most sub-Saharan African countries, some of the methods above may be inappropriate for obtaining realistic estimations. Therefore, Bayesian techniques, which are good for short data sets (Harjes and Ricci, 2010) could be useful to overcome estimation challenges that come with short data span. In addition, Bayesian techniques are recommended for data with long memory (Carlin, Dempster, and Jonas, 1985), as this may include financial and macroeconomic data that are reported to generally contain long memory attributes. Bayesian techniques, according to Kablan and Kaabia (2018), also accounts for nonlinearities, which may be present in data with long memory through the time varying aspects of the parameters.

The Bayesian approach to empirical analysis aims at establishing the probability of success given the results of independent draws or trials about a given phenomenon, and was proposed by Bayes in the paper; "An Essay Towards Solving a Problem in the Doctrine of Chances" (Bayes and Price, 1763). Bayesian econometrics is anchored on rules of probability, and involves parameter estimations of a given model, comparing different models or making forecasts (Koop et al, 2007). The Bayesian approach to empirical analysis uses a combination of a priori and post prior knowledge to model time series data. The approach allows the incorporation of prior knowledge researchers have

[40] See, for example Nyaga (2017), Sezgin and Atakan (2015), Eniekezimene (2013), Kemboi and Tarus (2012), Chukwuemeka et al. (2012), Yartey (2008), and el-Wassal (2005).

about the parameters requiring estimation, so as to aid the estimation process by learning from, and using, this knowledge to influence future estimations. This stands in contrast to the frequentist approach, which relies on repeating the event over and over in carrying out estimations (van de Schoot and Depaoli, 2014). Rahul et al. (2011) argues in favour of Bayesian inference stating that it has several benefits, including its ability to formalise the use of prior empirical or theoretical knowledge about the parameters of interest. In addition, these researchers advise that the use of such prior distributions makes the highly nonlinear optimisation algorithm considerably more stable, hence making it feasible to apply the technique when sample periods are short.

The Bayesian inference framework is a coherent one (Berti et al, 1991; and Winkler, 1967). This means that the framework is internally consistent (Kass and Wasserman, 1996). Unlike the frequentist approach to inference, the Bayesian approach has specific axioms related to rational decision making and therefore has no room for ad-hoc solutions aimed at correcting procedures that may lead to internally consistent outcomes.

The Bayesian approach involves marginalisation, which is done by integrating out unwanted (nuisance) parameters from the posterior distribution, based on the law of total probability (Koop et al, 2007). Through this, predictions can be made based on the predictive density. Model comparisons can further be made based on the Bayes factors, which are the ratio of two models' marginal likelihoods. Equally, one can estimate uncertainty (error) propagation.

Unlike the frequentist approach, the Bayesian approach can be used in non-nested models (Wang and Maruyama, 2016). This stems from the possibility to compute marginal likelihoods or marginal distributions on parameters of interest that, in turn, depends on the prior and the likelihood. In the Bayesian approach, there is no distinction between nested and non-nested models, and this advantage makes Bayesian techniques open to a wide possibility of use, unlike the frequentist method.

As Bayesian inference combines both data and prior information (Koop et al, 2007), several priors have been developed and admitted in Bayesian inference, depending on the issue the researcher wants to achieve. Two fundamental issues influence this:

i. Incorporating beliefs the researcher may have on the parameters of interest, and;

ii. Obtaining a well-behaved or correct posterior distribution.

Inappropriate use of priors might lead to incorrect inferences. Two broad categories of priors are used in empirical Bayesian analysis: *informative (elicited)* and *non-informative (diffused)* priors. A third category of priors, referred to as conjugate priors, is also common in Bayesian analysis, and is used to minimise the computational burden associated with Bayesian inferences. The *elicited (informative) priors* are the type with the most certain set of information about the parameter of interest, and have greater influential impact on the posterior distribution and thus on the final estimates (van de Schoot and Depaoli, 2014). The elicitation of information for use in empirical analysis is fundamental in Bayesian analysis. It has been used in Bayesian statistics were prior information is possible and acceptable, and data is limited (O'Hagan et al., 2006). The *diffused (non-informative) priors* do not state expressly the nature of information about the parameter of interest, and have been reported by Kass and Wasserman (1996) to dominate the posterior and leading to improper posteriors. Such priors are dominated by the likelihood. The *conjugate priors*, when combined with the likelihood, is the type that result in the posterior distribution that has the same class of distributions (Koop et al, 2007). This can be distinguished from the natural conjugate priors, which has the same functional form as the likelihood function. Unlike the conjugate priors, the natural conjugate priors are both able to make the interpretation and the computation of the posterior distribution easier (Koop et al, 2007).

In addition to statistical analysis, Bayesian techniques are also utilised in econometric analysis. The Bayesian vector autoregressive (VAR) models, such as the one used by Litterman (1986) and their variants, are now among the commonly estimated VARs using Bayesian techniques under different set of priors. This is for a number of reasons. First, estimating many parameters in the VAR model is a daunting task empirically. This is even worse if observations are few, which is often the case for many developing and emerging market economies. This can lead to the over-parameterisation of the VAR model. In this regard, the likelihood function is likely to be ill-behaved and thus, standard error for inferences from the VAR model may be large and insignificant (Cha and Bae, 2011). Bayesian techniques are able to overcome this through the use of Bayesian priors, as demonstrated by Litterman (1986). Second, unlike the classical approach that imposes strict restrictions on optimal lag length and the problem of unit root, the Bayesian approach is less restrictive and gets around these problems with the use of appropriate priors (Sims and Uhlig, 1991; and Cha and Bae, 2011).

The setting up of the priors in the estimation process in Bayesian VARs, in what has now come to be known as the Bayesian shrinkage approach, is a function of the various hyper-parameters. The hyper-parameters are so designed to reflect the informativeness of the prior distribution associated with a given model's coefficients (Giannone et al., 2014). In the past, setting of values for each hyper-parameter were done subjectively. However, Giannone et al (2015) have provided some theoretical grounding for setting the values for the hyper-parameters, and Korobilis (2016) guides on the use of priors in a Panel VAR setup.

While the original objective of Bayesian VARs was to improve macroeconomic forecasts, they have evolved to be useful for a variety of purposes in policy analysis. For example, the Bayesian shrinkage techniques have not just been used in modelling relationships for forecasting purposes, but also to generate impulse responses so as to shed light on the dynamic impact of shocks on one variable and how this affect others within the VAR framework (Fratzscher et al., 2010). For example, Kablan and Kaabia (2018) used the Bayesian shrinkage approach in modelling the transmission channels of international financial crises to African stock markets, with a focus on the euro sovereign debt crisis[41]. This study, however, did not use the *Calderon-Rossell* model. This work, nonetheless, demonstrates the value of Bayesian techniques in helping the understanding of how the dynamic behaviour of a shock to one variable can be transmitted to others within the VAR framework. In this regard, it is possible to apply the Bayesian shrinkage approach to the *Calderon-Rossell* model, and to estimate the impulse response of a shock to portfolio flows, and its impact on stock market capitalisation.

Nonetheless, a review of the literature revealed only one study that estimated the *Calderon-Rossell* model using Bayesian methods. This study, by Ng, Ibrahim and Mirakhor (2016), considered the *Calderon-Rossell* model and used Bayesian Model Averaging (BMA), but instead tested for FDI and not foreign portfolio equity flows, as one of the

[41] This is a departure from using Bayesian VARs for forecasting purposes as the case before.

determinants of stock market capitalisation for 60 developed and undeveloped countries[42]. Further, in this BMA estimation no impulse response functions (IRFs) were estimated to assess the dynamic impact of the shock to FDI and other determinants on stock market capitalisation. Thus, it may be necessary to extend this by including IRFs.

There are other techniques within the Bayesian framework that can generate IRFs and which makes tracing the effect of a shock on one variable on to the other variables over a defined time horizon possible. For example, Barboza and Vasconcelos (2019) estimated the IRFs in a large Bayesian VAR to determine the impact of the shock of the Brazilian Development Bank Loans (BL) on Brazil's Gross Fixed Capital formation (GFCF), the GFCF fraction of machinery and equipment (GFCFme), and the GFCF fraction of machinery and equipment manufactured in Brazil (GFCFmeBR). Further, Sims and Zha (1995) and Sims and Zha (1999) demonstrated the addition of error bands to IRFs, generated using Bayesian methods, as a way of incorporating uncertainties around the impulses, with these being referred to as credibility intervals (van de Schoot and Depaoli, 2014).

Bayesian techniques have further been found to be useful in generating impulse responses based on sign restrictions techniques to structural modelling, as argued by Moon and Schorfheide (2012). The sign restrictions are for the most part only well-defined within a Bayesian setup, and are based on the idea that structural shocks can be identified by determining whether the signs of the corresponding IRFs over a defined horizon are consistent with economic theory (Cha and Bae, 2011).

Traditionally, the shock identification procedure has been based on a Cholesky decomposition. Alternatively, short or long run restrictions have been used in recovering the structural shocks in line with Sims (1980), Bernanke (1986), and Blanchard and Quah (1989)[43]. However, the traditional methods to identification are not consistent with

---

[42] Argentina, Australia, Austria, Bangladesh, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Iran, Ireland, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Peru, Philippines, Poland, Portugal, Romania, Russian Federation, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Trinidad and Tobago, Turkey, Uganda, Ukraine, United Kingdom, United States, Venezuela, Vietnam, and Zimbabwe.

[43] Galí (1992)'s work on how well the IS-LM model fits the US data of the post-war era is based on this identification scheme, and thus accounts for among the early works on the implementation of the traditional identification scheme.

standard dynamic stochastic general equilibrium (DSGE) models and a sign restriction estimation procedure. Alternative identification schemes, credited to Faust (1998), Canova and Nicoló (2002) and Uhlig (2005), have been developed to aid the identifications consistent with DSGE and Bayesian approach with sign restrictions (Danne, 2015). This is accomplished by first estimating the VAR with Bayesian techniques and using the resulting impulses, derived through the Cholesky decomposition, to interact with the sign restriction based on the Given's rotation matrix to create candidate structural shocks (Fry and Pagan, 2011). Using Bayesian techniques as well (involving the Markov Chain Monte Carlo (MCMC) process), draws are made for the new set of impulses that satisfies the sign restriction (Danne, 2015).

Fry and Pagan (2011), as well as Kilian and Murphy (2012), have suggested going beyond sign restrictions by using extra information. The Uhlig (2005) penalty – function method imposes more than just sign restriction to overcome the problem of many candidate impulse vectors, which is not the case with the Uhlig (2005) rejection method. The method penalises responses that do not satisfy sign restrictions and rewards those that do, by more heavily penalising the former than it rewards large and correct responses. In other words, it punishes larger deviations more than smaller ones. The method minimises a criterion function that penalises for sign restriction violations (Danne, 2015).

Since the pioneering works of Dwyer (1998), Faust (1998), Canova and Nicoló (2002) and Uhlig (2005)[44], and early application in empirical work by Peersman (2005), sign restrictions in shock impact and transmission modelling within a structural VAR setup estimated with Bayesian techniques have proliferated in literature[45]. The Bayesian approach to modelling economic relationships for generating impulse responses is not just based on Bayesian shrinkage or use of sign restrictions only. A number of studies have also used a mixed method involving sign and zero restrictions in order to address particular research questions, in the spirit of Kilian and Murphy (2012), Canova and Nicoló (2002), and Uhlig (2005). This involves imposing zero restrictions on parameters that have a contemporaneous impact to obtain impulse response results that are

[44] First appeared as a CentER Working Paper 9928), Tilburg University, in 1999.

[45] See, for example, Robstad (2018), Kim and Lim (2018), Cha and Bae (2011), Tamási and Világi (2011), Busch et al. (2010), and Chadha et al. (2010).

consistent with economic theory, as shocks to some variables manifest with a delay (Fisher and Huh, 2020) and also shocks from some variables affect others with a lag as they interact with each other as a system. Among those that have used this approach are Arias et al. (2018), Kabashi and Suleva (2016), and Kilian and Murphy (2012). This demonstrates the versatility of the Bayesian technique in applied research and indicates that the technique could be amenable to estimating different economic relationships, including estimating the *Calderon-Rossell* model in which foreign portfolio flows is one of the candidate variables used, and further generating impulse response functions.

The flexibility and usefulness of Bayesian methods with sign restrictions (including zero restrictions) can be seen, albeit with limited use so far, in analysing the dynamic impact of asset prices and foreign capital flows on macro and microeconomic variables, either in a DSGE or structural vector autoregression (SVAR) setup (see for example Sá, et al., 2014; and Fratzscher and Straub, 2009). The application of Bayesian techniques is prevalent in the DSGE and SVAR models as they help identify structural shocks and trace their propagation (including contagion effects) over time (even in panel setups), as for example demonstrated by Shu et al. (2018); Granziera, Moon, and Schorfheide (2018); Sá and Wieladek (2015) and Hristov, Hülsewig, and Wollmershäuser (2012)

The flexibility of Bayesian methods in empirical work makes it ideal for investigating how shocks in financial and economic related transactions affect foreign capital flows in a Bayesian framework with sign restrictions, and to trace their impact on selected financial and economic data. In this regard, Bayesian techniques with sign restrictions could be successfully applied to the *Calderon-Rossell* model and assess the impact of foreign portfolio flows on stock market capitalisation. This potentially builds and improves on the works of Ng, Ibrahim and Mirakhor (2016), who used Bayesian techniques to study the effect of capital flows on stock market development based on the *Calderon-Rossell* model, and Nyaga (2017), Sezgin and Atakan (2015), Eniekezimene (2013), Kemboi and Tarus (2012), Chukwuemeka et al. (2012), Yartey (2008), and el-Wassal (2005), who conducted similar studies within the *Calderon-Rossell* framework. As previously indicated, none of the above studies investigated the dynamic impact of these foreign flows on stock market development over time by way of impulse response functions.

2.7. Use of Gross Flows versus Net Flows

Past empirical studies on capital flows generally focused on gross inflows and net flows, and rarely on the gross outflows (Guichard, 2017). This is despite the possibility that gross outflows may have the capacity to offset or magnify the impact of gross inflow fluctuations (Guichard, 2017). However, after the global financial crisis, there is now an increasing interest in looking at the gross outflows as well, particularly following Forbes and Warnock (2012)'s argument in favour of the use of gross flows, which they found to provide more insights than in the case of using net flows.

Additionally, gross capital inflows and outflows are now considered to generally be more volatile than net capital flows, which reflects co-movement between capital inflows and outflows. This implies a need to also study gross outflows, especially in view of the sudden stop and retrenchment behaviour of these foreign capital flows (Davis, Valente and van Wincoop, 2019). For example, Eichengreen et al. (2017) used both gross inflows and outflows separately in a cross-country panel estimation in an attempt to understand risk aversion, and concluded that emerging markets' non-FDI outflows tended to respond negatively to global risk aversion, but that non-FDI inflows were more responsive to pull factors. This supports the perception that gross inflows and the gross outflows may have different characteristics. Specifically, Eichengreen, Gupta, and Masetti (2017) argued in favour of analysts and policy makers also taking interest in gross capital outflows given their roles in economies.

Further, the IMF (2016) recently empirically examined gross inflows and gross outflows separately, although reported difficulties in interpreting the results on the gross outflows compared to the gross inflows. On the other hand, earlier works involving Forbes and Warnock (2012) and Broner et al. (2013), and recent empirical works by Lafuerza and Servén (2019), Davis, Valente and van Wincoop (2019), Eichengreen, Gupta, and Masetti (2017), and Eichengreen et al. (2017) reported no such interpretational difficulties. Therefore, it is important to analyse both gross outflows and gross inflows, especially if the empirical work being undertaken on capital flows is intended to generate policy relevant insights aimed at managing both types of foreign capital flows.

2.8. Structural Breaks and Time Series Data

Structural breaks are seemingly pervasive in economic and financial time series data[46]. Although these structural breaks were initially detected in the data for the Western, Asian, and Pacific countries, the problem does also exist among sub-Saharan Africa countries' data. For example, Ikwor and Nkama (2018) detected structural breaks in Nigeria's macroeconomic and financial data (interest rates, exchange rate and inflation) with an advise to modellers, in light of these results, to consider using regime switching models when working with the Nigerian data to avoid misleading results.

Similarly, Olufemi, Adewale, and Oseko (2017) tested for structural breaks in the foreign exchange returns for 10 sub-Saharan Africa countries in the course of examining the efficiency of the foreign exchange markets of these countries. An important aspect of the results from this study, which are vital on the importance of accounting for structural breaks in time series data, is that disregarding structural breaks in the test only led to two foreign exchange markets out of ten being found to be efficient. However, when the respective structural breaks were accounted for, like before, only two foreign exchange markets were found to be efficient before and after the structural break, but only a further two foreign exchange markets were not efficient prior to and after the respective structural breaks. However, the remaining six foreign exchange markets had mixed results. The study arrived at the conclusion that ignoring the presence of structural break may lead to misleading results, and by extension this therefore can also result in a sub-optimal policy action.

Structural breaks in the data occurs if there is a change at some date in the parameters – mean, variance, and trend - of the model governing the evolution of the data, as these parameters are expected to be stationary throughout (Hansen, 2001). Structural breaks can lead to misleading empirical based policy advice if ignored, because of their ability to distort statistical inferences (Hansen, 2001).

In view of this, a number of methods have been developed to help identify structrural breaks in time series data since the pioneering works of Quandt (1958) and Chow (1960).

[46] See, for instance, Lee and Chou (2020), Hegerty (2020), Maria and Luis (2020), Preuss et al. (2015), Rapach, Wohar, and Wohar (2005), Hansen (2001), Bai and Perron (1998), and Andrews and Ploberger (1994).

This proliferation has led to different classification of such methods that include those tests that are possible with known breakpoints, and those that can be undertaken with unknown breakpoints to the researcher. Within these classes, there are those with single and those with multiple breakpoints. For a detailed description and recent review of these methods together with their pros and cons, Muthuramu and Uma-Maheswari (2019) provides valuable information for both old and recent test methods.

For empirical analysis aimed at generating policy relevant information, in view of the findings by Olufemi, Adewale, and Oseko (2017), for example, that shows different estimation results when and when not structural breaks are accounted for, a multiple breakpoints estimation procedure such as the ones developed and/or applied by Jouini and Boutahar (2005); Zeileis, et al. (2002); and Bai and Perron (1998), can be of great help. Fundamentally, the problem with structural break tests yielding single breakpoints is when the breakpoint estimated is located towards the end of the sample (the 'relevant past') such that the number of observations available are too few for meaningful empirical analysis aimed at generating policy relevant information on the basis of relelatively recent data. In this regard, methods yielding multiple breakpoints are preferable as the researcher can (even arbitrarily) choose a break point further back in the series that can give sufficient observations for a meaningful empirical analysis of the period after the researcher's identified structural break. The drawback with this approach however, is that the data used in that case may also include the ones for the immediate past regime, and the sample in this context will not entirely reflect the current regime.

Test procedures for multiple breakpoints involve the use of a generalised fluctuation framework such as done by Leisch, Hornik, and Kuan, (2000); and Kuan and Hornik (1995), for example. This contrasts the F-Statistic based tests (usually common for single breakpoints identification) as, for instance, associated with Andrews and Ploberger (1994). Meanwhile, there are also other procedures based on Maximum Likelihood (ML), such as one by Hansen (1992) as well as Nyblom (1989), and Bayesian based techniques that includes the work by Yin (1988), and Yao and Au (1989). However, to benefit from more information on the structural break test results, a procedure that combines the features in the methods highlighted above is vital. Thankfully, Zeileis et al. (2002) have developed a routine that combines features from the generalised fluctuation framework and F-Statistics that is easily implemented in Studio R under the package *strucchange.* An updated version of this has been developed by Zeileis et al. (2003). Zeileis (2005) has combined features from the generalised fluctuation framework, ML, and F-Statistics , arguing that these tests are more related to each other, although developed for different alternatives. These frameworks open an opportunity of using a structural break test procedure that is more informative, as they contain more features.

2.9. Chapter Summary

From the literature it is clear there is no consensus on the best approach to deal with foreign capital flows and the challenges associated with these flows. This could in part be due to the lack of a clear understanding of the underlying processes assumed by these flows, and the application of such an understanding to their management. Further, for portfolio equity flows, especially in the context of sub-Saharan African stock markets that need these flows to augment liquidity, a better understanding of their dynamic impact on stock market capitalisation, and thus stock market development, could better inform appropriate policy approaches to the management of the foreign portfolio equity flows.

Both the theoretical and empirical literature on capital flows have largely focused on the determinants of these cross-border flows. In addition, the empirical literature has also explored aspects of volatility of these flows, as well as the impact of these flows on macroeconomic variables. Further, the very limited empirical literature on the underlying process of foreign capital flows has made little connection to the control or management of these foreign capital flows. Recently, the underlying process of foreign capital flows has been estimated by determining the Hurst parameter, a measure of long-range dependence, of these flows. However, it is generally not recommended that the Hurst parameter be estimated without understanding the class to which of the fractal signals it belongs (Serinaldi, 2010 and Eke et al., 2002).

Signal class distinction is made between fractional Gaussian noise (fGn) and fractional Brownian motion (fBm), popularised by Mandelbrot and Van (1968). Importantly, Cannon et al. (1997) established that it is possible for empirical analysis to yield the same Hurst parameter estimate for both an fGn and fBm signal despite them being different signals, thus risking obtaining a spurious Hurst parameter estimate. Understanding the fractal signal classification can therefore help with the correct interpretation of the estimated Hurst parameter.

Furthermore, knowledge and understanding of the underlying process of foreign capital flows, and particularly foreign portfolio equity flows, may not be sufficient in deciding on the optimal policy approach to the control or management of, particularly, the foreign portfolio equity flows. An understanding of the dynamic impact of these flows on stock markets' capitalisation, and thus stock market development, may be useful additional information to inform the policy process relating to the management of the gross foreign portfolio equity flows. Much theoretical work related to the *Calderon-Rossell* model, showing that stock market capitalisation is determined by economic growth and stock market liquidity, as well as empirical modifications of this model using other variables of interest such as foreign capital flows, is found in the literature. However, prior estimations of the *Calderon-Rossell* model have generally not utilised methods that allow for a better understanding of the dynamic impact of shocks to capital flows on stock market capitalisation. A possible candidate estimation method to achieve this is Bayesian techniques, which are ideal for the short data series that characterise most SSA countries.

Besides the underlying process and the impact of foreign portfolio equity flows on stock market development, structural breaks should also be considered when considering an optimal policy intervention on foreign portfolio equity flows since structural breaks may undermine the estimation results. If not, policy advice may be misleading and thus sub-optimal, to the disadvantage of stock market development.

Chapter 3 that follows discusses and undertakes some statistical diagnostic tests on the data used in this study, with a specific focus on gross foreign portfolio equity inflows and gross foreign portfolio equity outflows, the two candidate variables for the study on the underlying process undertaken in Chapter 4. This is also extended to other variables – macroeconomic and stock market indicators – identified based on the review of literature presented in the present Chapter, to be used for the further empirical analysis undertaken in Chapter 5.

Chapter 3
Data Description and Diagnostics

3.1. Introduction

This chapter presents a description of the variables and the statistical properties of the data used to investigate the underlying process of the gross foreign portfolio equity inflows and outflows, as well as their impact on stock market development. Different statistical techniques are employed to help understand the characteristics of the data. Further, particularly for the foreign portfolio equity inflows and foreign portfolio equity outflows, autocorrelations and structural break tests are undertaken to establish a preliminary understanding of their underlying process in view of possible structural breaks.

3.2. Description of Variables and Data Sources

The variables of interest in this study are foreign portfolio equity inflows (FPEI), foreign portfolio equity outflows (FPEO), and market capitalisation (a stock market development indicator). However, other variables are also used to help address the research objectives and related research questions in this study. The choice of other variables is guided by literature contained in the previous chapter and specifically relates to the works by Sezgin et al. (2015), Yartey (2010), Yartey (2008), and el-Wassal (2005). These other variables are exchange rates, inflation, stock market turnover, and real economic activity indicators, which interact with the three variables of interest in order to establish the impact of the foreign portfolio equity flows on stock market development. Table 3.1 provides the list of variables and their description, as well as the source of their data.

Table 3.1: Variables and Data Sources

Country	Variable	Description	Source	Coverage
Kenya	FPEI	Foreign investors' purchase of shares on the Nairobi Securities Exchange (NSE). The value of the inflows is in United States Dollar (USD) converted from the Kenyan Shilling value using the corresponding period exchange rate by way of dividing the former by the latter.	Kenya's Capital Markets Authority (CMA)'s Quarterly Statistical Bulletin (QSB), various issues.	January 2011 – September 2018.
	FPEO	Sale of shares by non-residents at the NSE and its values (also in USD) are derived in a similar way as above.	CMA's QSB, various issues.	Same period as above.
	Market Capitalisation	This is the market capitalisation (MktCap) of the entire Nairobi's securities exchange. It is a sum of individual companies' market capitalisations measured as share price (ρ) multiplied by outstanding shares (Φ) of a given company. i.e. MktCap = $\sum_{i=1}^{n}[(\rho_i) \times (\Phi_i)]$ The value is in USD derived as a quotient of its shilling value and the Kenya Shilling/USD exchange rate ruling at the time.	CMA's QSB, various issues, for MktCap and Central Bank of Kenya (CBK) for the exchange rates.	Same period as above.
	Market Turnover	Value of shares traded on the NSE, and are in USD obtained by dividing its value by the Kenyan Shilling/USD exchange rate of the related month.	CMA's QSB (various issues) and the CBK.	Same period as above.
	Economic Activity	This is proxied as real private sector credit (RPSC) measured as private sector credit (PSC) normalised by the consumer price index (CPI),	CBK for the PSC data and Kenya National Bureau of	Same period as above.

		i.e. RPSC = PSC/CPI	Statistics (KNBS) for the CPI data.	
	Exchange Rate	Value of the Kenyan shilling per one USD.	CBK	Same period as above.
	Headline Inflation	Annual percentage change in the Kenyan CPI	KNBS	Same period as above.
Nigeria	FPEI	Purchase transactions of equities by foreign participants on the Nigerian Stock Exchange (NgSE). The values are in USD dollar computed by dividing their Naira value by the exchange rate of the Naira to the USD.	NgSE Domestic and Foreign Portfolio Investment report (various issues).	March 2013 – March 2019.
	FPEO	Sales transactions or liquidation of portfolio investments by foreign participants through the NgSE. The values are also in USD obtained as per procedure used for the FPEIs' counterpart.	NgSE Domestic and Foreign Portfolio Investment report (various issues).	As above.
	Market Capitalisation	Same definition as for Kenya's, and its value is in USD. This is derived by dividing its Naira value by the exchange rate prevailing at the time.	Central Bank of Nigeria (CBN).	As above.
	Market Turnover	Value of total equity transactions at the NgSE. They are in USD computed as a quotient of their Naira value and exchange rate of the Naira and the USD.	NgSE Domestic and Foreign Portfolio Investment report (various issues).	As above.

	Economic Activity	Described and treated in the same way as Kenya's	CBN for the PSC data and Nigeria's National Bureau of Statistics (NBS) for All Items CPI data.	As above.
	Exchange Rate	Value of the Naira per one USD.	CBN	As above.
	Headline Inflation	Annual changes in the Nigeria's All Items CPI expressed in percentage terms.	NBS	As above.
South Africa	FPEI	Purchase of South African equities at the JSE by non-residents. The data is in US dollar (USD) and obtained by dividing the Rand values by the period exchange rate.	South Africa Reserve Bank (SARB).	January 1994 – April 2018
	FPEO	Sale of equities at the JSE by non-residents. This data is also in USD, obtained in a similar way as the case for the FPEIs.	SARB	Same period.
	Market capitalisation	This is as defined before. It is measured in USD and obtained by dividing its Rand value with the exchange rate obtaining at the time.	SARB	Same period.
	Market turnover	See definition above. The value is in USD obtained by dividing its Rand value by the period exchange rate of the Rand to the USD.	SARB	Same period.
	Economic Activity	The proxy used is the monthly Physical volume of manufacturing production (PVMP). It is a widely used	SARB	Same period.

		proxy for South Africa's GDP which is measured on quarterly basis.		
	Exchange rate	This is the value of the Rand per one USD.	SARB	Same period.
	Headline Inflation	Annual percentage change of the South African consumer price index.	Statistics South Africa (SSA).	Same period.
Zambia	FPEI	Buying of shares at the Lusaka Securities Exchange (LuSE) by foreign investors. The values are in USD as reported by the Zambian authorities.	Bank of Zambia (BoZ).	January 2007 – September 2018.
	FPEO	Selling of shares on the LuSE by foreign investors. Values are also in USD as reported by the authorities.	BoZ	Same as above.
	Market Capitalisation	Defined as before, with values in USD as reported by the authorities.	BoZ	Same as above.
	Market Turnover	Same as above. The values are in USD and in line with the authorities' reporting currency.	BoZ	Same as above.
	Economic Activity	Also proxied by RPSC and computed in a similar manner as Kenya and Nigeria's.	BoZ for PSC data and the Zambia Statistical Agency (ZamStat) for the All Items CPI data.	Same as above.
	Exchange Rate	Value of the Zambian Kwacha per one USD.	BoZ	Same as above.
	Headline Inflation	Annual changes in the Zambian All Items CPI multiplied by 100 percent.	ZamStat	Same as above

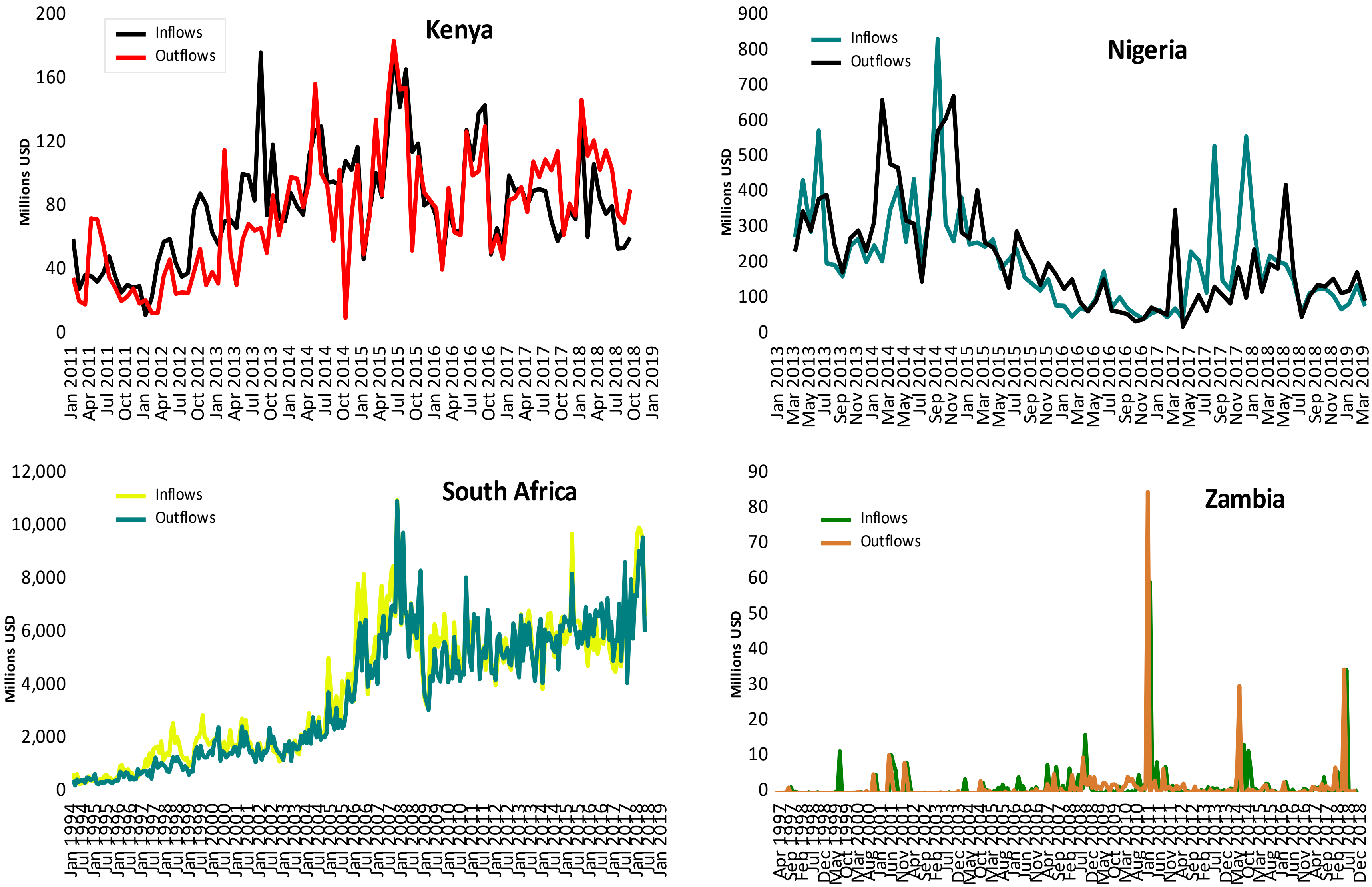
Source: Author

3.3. Foreign Portfolio Equity Flows Data

3.3.1 Trending Behaviour

The gross foreign portfolio equity flows associated with Kenya, Nigeria, South Africa, and Zambia display mixed behaviour (Figure 3.1). Both the inflows and outflows for South Africa trend upwards, although fluctuating, from January 1994 onwards, until disrupted in around July 2007 and May 2009, when they declined sharply. This period coincides with the sub-prime crisis and the global financial crisis. However, from about July 2009, both flows bottomed out and resumed an upward trend, with a relatively large decline only observed at the end of the sample period. Similarly, an upward trend largely characterises Kenyan inflows and outflows from January 2011, the start of the sample period. This upward trend got disrupted after May 2015, as both the inflows and outflows declined. After October 2016, both the inflows and the outflows remained lower than the high levels recorded in mid-2015.

In the Nigerian sample, spanning March 2013 to March 2019, spikes are observed in both inflows and outflows. However, a declining trend can be seen for both type of flows starting from around January 2015 to around February 2017. In contrast, Zambian flows have largely been flat and small in magnitude but includes some huge spikes for both foreign portfolio equity inflows and outflows, with the latter having a relatively larger spike around December 2010. The latter likely arises from the purchase of 908,567,344 shares in a mandatory offer (MO) to minority shareholders by Bhati Airtel Zambia BV (a company incorporated in Netherlands), including non-residents' sale participation in the months of November-December 2010. After the transaction, some foreign investors may have purchased other LuSE listed shares out of the proceeds, which may have led to the spike in the inflows during the same period.

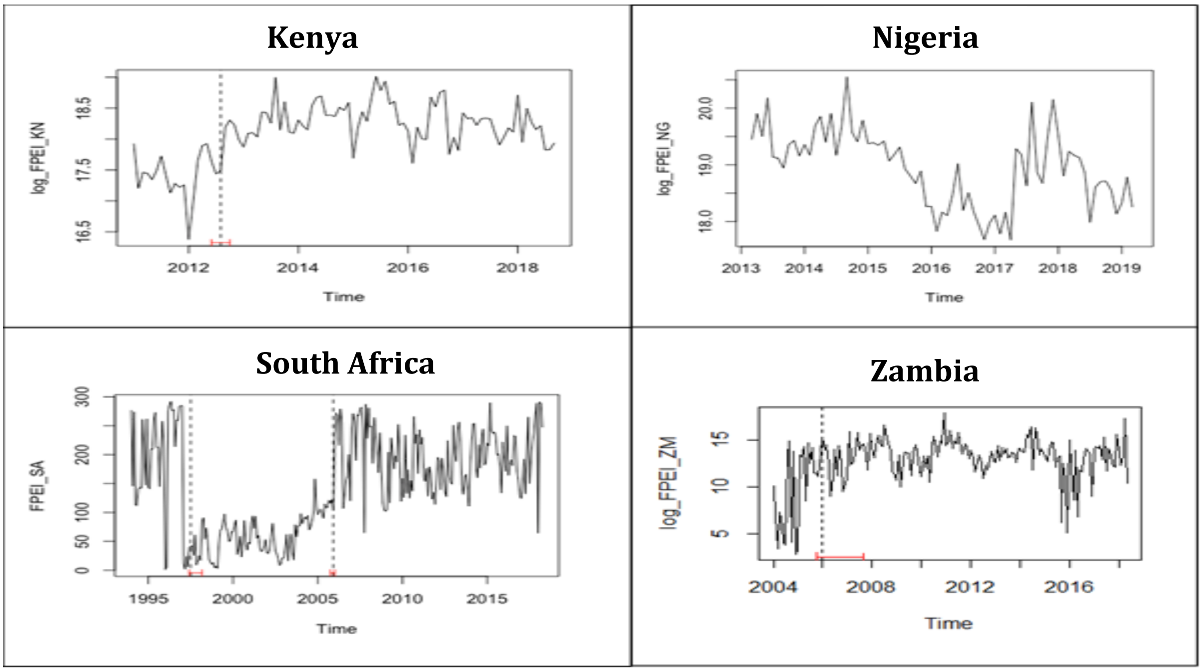


Source: CMA, NgSE, SARB and BoZ

Figure 3.1: Foreign Portfolio Equity Flows.

3.3.2. Potential Structural Breaks

Studio R's package *strucchange* was used to identify structural breaks for the four countries FPEI and FPEO data, which are summarised in Figure 3.2a and Table 3.2a. Four FPEI structural breaks were identified as being significant (97.5% confidence interval) for South Africa, and none for the Kenyan, Nigerian and Zambian data in levels, but after taking logs on the three series, two structural breaks, in each case, were detected for Kenyan and Zambian data only.



Source: Author, Studio R strucchange Package output.

Figure 3.2a: Foreign Portfolio Equity Inflows Structural Break Points

Table 3.2a: Structural Break Tests for FPEI

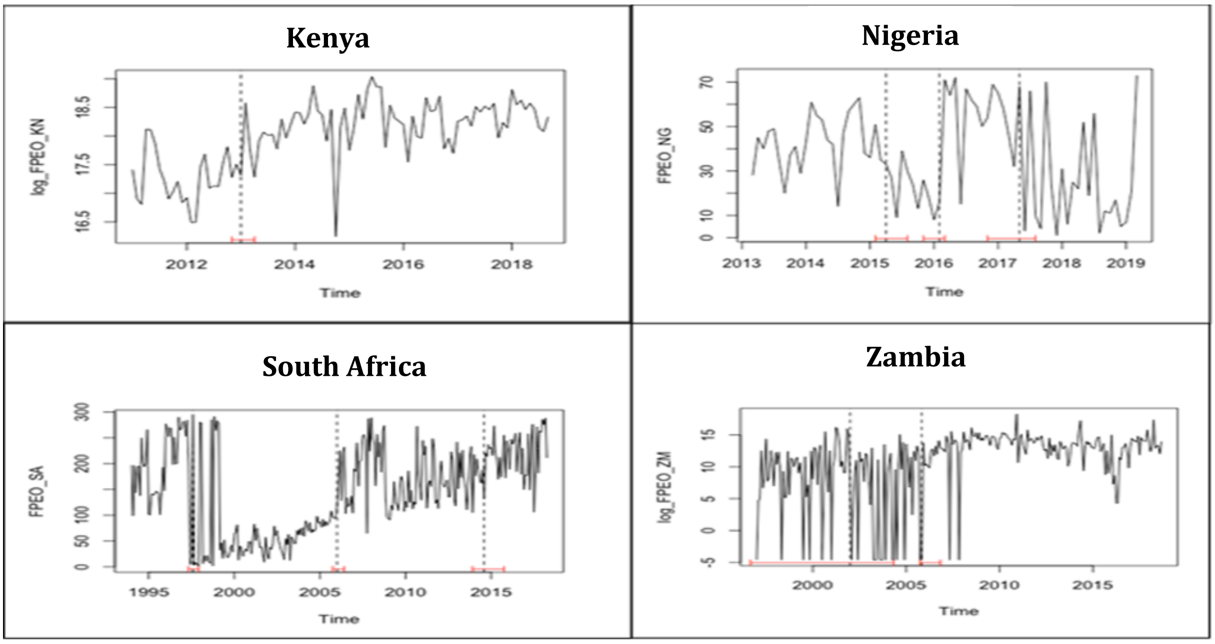
Country	Confidence Interval (%)	Observation Point	Observation Date
Kenya	2.50	18	June 2012
	97.5	20	August 2012
		22	October 2012
South Africa	2.50	42	June, 1997
		142	October, 2005
	97.50	43	July, 1997
		51	March, 1998
		144	December, 2005
		145	January, 2006
Zambia	2.50	22	October 2005
	97.50	25	January, 2006
		45	September, 2007

Source: Author, Studio R strucchange Package output.

The structural breaks identified for Kenya in August and October 2012 could be related to political uncertainty, given that the country held its general elections in 2012 and the previous election was violent and disruptive to the economy. Additionally, in August 2012 there were some tribal clashes in the Tana River District in eastern Kenya with at least 50 people confirmed dead, a situation that could have been linked to political violence and therefore a political risk factor to investors. This in turn may have contributed to the foreign portfolio investors reduced exposure to Kenya. Therefore, these developments may have posed the political risks that could have led to change in behaviour of the foreign capital flows leading to the structural breaks in the foreign portfolio equity inflows to Kenya.

The South African structural breaks around December 2005 and January 2006 were due to the unusual increase in the inflows. This could have been due to strong economic fundamentals and favourable investor perception associated with South Africa at the time (SARB, 2006a), given strong economic performance and GDP growth of 5.0 percent in 2005, an improvement from the 4.5 percent recorded in 2004 (SARB, 2006b). In the case of Zambia, its foreign debt write off under the Highly Indebted Poor Countries Initiative scheme of the World Bank and the International Monetary Fund (Bank of Zambia, 2006) may have induced favourable investor perception towards Zambia. This partly led to the increase in the foreign portfolio equity inflows by at least 456.9 percent (to US $4.6 million) during the period.

With regard to the foreign portfolio equity outflows, two significant structural breaks in log transform were identified for Kenyan (Figure 3.2b and Table 3.2b). Six structural breaks were identified for the Nigerian data, and the same number for the South African series. Zambia's data, when transformed in logs, display four structural breaks. With the exception of Kenya, more structural breaks were found in the outflows than the inflows for the other three countries, suggesting that foreign portfolio equity outflows experienced more shocks in Nigeria, South Africa and Zambia than the foreign portfolio equity inflows.



Source: Author, Studio R strucchange Package output.

Figure 3.2b: Foreign Portfolio Equity Outflows Structural Break Points

Table 3.2b: Structural Break Tests for FPEO

Country	Confidence Interval (%)	Observation Point	Observation Date
Kenya	2.50	23	November 2012
		25	January 2013
		28	April 2013
Nigeria	2.50	24	February 2015
		33	November 2015
		45	November 2016
	97.50	26	April 2015
		30	August 2015
		36	February 2016
		37	March 2016
		51	May 2017
		54	August 2017
South Africa	2.50	41	May, 1997
		142	October, 2005
		240	December 2013
	97.50	44	August, 1997
		48	December, 1997
		145	January, 2006
		150	June 2006
		248	August 2014
		262	October, 2015
Zambia	2.50	9	September 1997
		106	October 2005
	97.50	61	January, 2002
		89	May 2004
		107	November 2005
		119	November, 2006

Source: Author, Studio R strucchange Package output.

The relatively high number of structural breaks in the outflows data for three countries could be due to the exchange rate volatility associated with commodity prices driven currencies. The three countries are extractive commodity exporting economies (oil for Nigeria, gold and platinum for South Africa, and copper for Zambia). Thus, volatility associated with commodity prices and their adverse impact on the exchange rates for the SSA commodity price driven currencies (the Nigerian Naira, South African Rand, and Zambian Kwacha) may have posed risks leading to the increase in outflows, since investors prefer an environment with a stable exchange rate (Hu et al., 2016). The visualisation of data in Figure 3.5a in Section 3.5 of this chapter shows how the three currencies have depreciated over the period.

Considering the significant structural breaks in the data for each country and class of flows, sub-samples with enough observations to undertake further empirical analysis can be identified. This may help gain more insights on the behaviour and impact of foreign portfolio equity flows on stock markets in the four SSA countries for the overall sample and the sub sample, particularly one with relatively recent data ('the relevant past'). This may be necessary for optimal policy intervention in case there are different regimes characterising the data generating process in each segment on the either side of the structural breaks.

In view of this, taking the breakpoint around December 2005 and January 2006 as the distinguishing period for South Africa's foreign portfolio equity inflows, here after referred to as *SA_Fepi_Jan2006StrBrk*, two sub-samples with sufficient observations emerge. The choice of the two structural breaks as reference points is not just for obtaining sufficient observations that could make empirical work feasible but also, in the case of the period after the identified reference structural break, covers the fairly recent capital flows related crises identified by Ghosh, Ostry, and Qureshi (2016)[47].

These crises include the sub-prime crisis of 2007 that culminated into the global financial crisis of 2008-2009, and that led to the inception of the unconventional monetary policy (UMP) by the US Federal Reserve Bank (FRB), the euro debt crisis of 2012, and the taper

[47] In literature, this work gives a detailed enumeration of the shocks and crises that have led to foreign capital flows volatility and crises.

tantrum of 2013 that was later followed by the FRB monetary policy normalisation[48] induced capital flow crisis of 2015. Therefore, the first sample based on the referenced structural break is for the period January 1994 to December 2005 and the second is from February 2006 to April 2018. Crises associated with the overall sample also applies to the post structural break data set.

Similarly, partitioning South Africa's foreign portfolio equity outflows series into two parts for the same reason as advanced in favour of the foreign portfolio equity inflows by adopting a significant structural break recorded in January 2006, here after referred to as *SA_Fepo_Jan2006StrBrk*, two sub-samples can be distinguished. As with the inflows, these cover the periods January 1994 to December 2005, and from February 2006 to April 2018.

When the same procedure above is done for Kenya's data, its first significant structural breaks in respect of the FPEIs and FPEOs can be taken as reference points, given the relatively small sample size, but more importantly, covers the euro debt crisis, the taper tantrum and the unwinding of the UMP. The identified structural breaks are here referred to as *Kn_Fepi_Aug2012StrBrk* and *Kn_Fepo_Jan2013StrBrk*, respectively. In each case, the samples before the structural breaks may be too short for any meaningful empirical analysis compared to the period after.

Concerning Nigeria, since the inflows have no structural breaks, only the outflows can be partitioned and, in this regard, the first observed structural break can be the point of reference, given the short span of the data, but more importantly, this sub-sample has the UMP shock induced crisis captured in the data. This identified structural break is referred to as *Ng_Fepo_Apr2015StrBrk*. For Zambia, and given its relatively long series, the January 2006 and November 2006 structural breaks for the FPEIs and FEPOs, respectively, are appropriate reference points that cover the shocks or crises that induced the foreign capital flows concerns identified by Ghosh, Ostry, and Qureshi (2016), as is the case with the South African data. Hence, the respective referenced structural breaks can be regarded as *Zm_Fepi_Jan2006StrBrk* and *Zm_Fepo_Nov2006StrBrk*. The respective sub-samples in respect of the inflows are January 1997 to December 2005 and February 2006

[48] That is marking the end to UMP.

to September 2018. For the outflows, the two sub-samples therefore cover the period January 1997 to October 2006, and December 2006 to September 2018.

3.3.3. Descriptive Statistics

The descriptive statistics show that South Africa had the highest volume of gross inflows, amounting to US $11.1 billion, and averaging US $3.9 billion per month over its sample period. This is followed by Nigeria in distant second place, with its highest level of gross inflows amounting to US $839.1 million and averaging US $210.1 million per month for the considered sample period (Table 3.3a). Zambia has the lowest amount of gross inflows, with an average of US $1.6 million per month over its sample period, and the highest being US $59.8 million.

Table 3.3a: FPEI Descriptive Statistics - Overall Sample

Description	Kenya	Nigeria	South Africa	Zambia
Mean*	80.53609	210.1408	3,914.827	1,616.656
Median*	78.43566	190.9822	4,265.650	338.5807
Maximum*	180.7379	839.1330	11,061.50	59,780.78
Minimum*	12.94836	47.39336	379.0304	1.000000
Standard Deviation	34.73165	144.5595	2,427.878	4,814.242
Skewness	0.602021	1.720635	0.273915	8.436352
Kurtosis	3.291008	7.104359	2.133525	92.01881
Jarque-Bera (JB)	5.945808	87.25962	12.78590	89273.27
Probability	0.051155	0.000000	0.001673	0.000000
Observations	93	73	292	261

* Values are in millions of US Dollar, except for Zambia, whose flows are in thousands of US Dollar
Source: Author, EViews output.

South Africa's gross inflows are nearly symmetrical, with a skewness of near zero. This is not the case with the other three countries. However, its standard deviation is only second to that of Zambia, which has the largest computed standard deviation. Kenya has the least variability and hence the smallest standard deviation of the four countries. Nonetheless, all four countries' data is non-normal, as indicated by the respective Kurtosis values that are not equal to 3.0, and as shown by the respective high Jarque-Bera (JB) statistics.

Accounting for structural breaks; *Kn_Fepi_Aug2012StrBrk, SA_Fepi_jan2006StrBrk,* and *Zm_Fepi_Jan2006StrBrk,* the descriptive statistics show that the gross inflows experienced the highest volume in the periods after the respective countries' structural break points (Table 3.3b). On average, the gross inflows were higher in the post structural break era for each country as a result. However, it is worth noting that none of the sub-sample series are normally distributed, and for each country the sub-sample distributions are right skewed in their asymmetric disposition (in contrast to the overall sample South African gross inflow data, which has a skewness of almost zero).

Table 3.3b: FPEI Descriptive Statistics - Sub - Samples

Description	Kenya	South Africa		Zambia	
	After	Before	After	Before	After
Mean*	92.00005	1,752.087	6,017.495	764.2340	2,202.406
Median*	85.06287	1,662.095	5,865.910	39.90246	778.6405
Maximum*	180.7379	5,109.430	11,061.50	1,1960.53	59,780.78
Minimum*	44.42177	379.0300	3,342.060	1.000000	1.983000
Standard Deviation	29.68098	972.4190	1,311.561	2,124.476	5,981.911
Skewness	0.984948	0.920576	1.183666	3.681535	7.209706
Kurtosis	3.778416	3.972185	5.263153	16.46309	63.63241
Jarque-Bera (JB)	13.64620	26.00991	65.69747	1059.613	24,599.99
Probability	0.001088	0.000002	0.000000	0.000000	0.000000
Observations	73	144	147	108	152

* Values are in millions of US Dollars save for Zambia whose values are in thousands of US dollars.
Source: Author, EViews output.

With regards to gross foreign portfolio outflows, South Africa outflows, as with inflows, are the largest among the four countries, with an average of US $3.7 billion per month and a maximum of US $11.0 billion per month (Table 3.4a). As with the inflows, South African and Zambian gross outflows are more variable than that of Kenya and Nigeria. South Africa and Kenya's gross foreign portfolio equity outflows show signs of being symmetrical, but Nigeria and Zambia's outflows are right skewed. However, the kurtosis and JB Statistics suggest that only the series for Kenya is normally distributed.

Table 3.4a: FPEO Descriptive Statistics - Overall Sample

Description	Kenya	Nigeria	South Africa	Zambia
Mean*	75.97790	219.3328	3,712.827	1,527.427
Median*	75.94962	179.5720	3,929.030	321.4490
Maximum*	185.3334	677.7689	11,015.16	85,194.11
Minimum*	11.30824	25.78277	312.7900	1.027000
Standard Deviation	38.34358	150.1615	2,423.007	6,120.156
Skewness	0.380901	1.229018	0.286071	10.92628
Kurtosis	2.694441	4.211165	1.958051	140.3248
Jarque-Bera (JB)	2.610623	22.83945	17.19155	210,275.0
Probability	0.271088	0.000011	0.000185	0.000000
Observations	93	73	292	261

* Values are in millions of US Dollars save for Zambia whose values are in thousands of US dollars
Source: Author, EViews output.

When the structural breaks *SA_Fepo_Jan2006StrBrk*, *Kn_Fepo_Jan2013StrBrk*, *Ng_Fepo_Apr2015StrBrk*, and *Zm_Fepo_Nov2006StrBrk* are accounted for, South Africa and Zambia recorded more gross outflows in the era after the identified structural breaks. Further, none of the sub-samples are normally distributed, and all the series are positively skewed and thus non-symmetrical (Table 3.4b).

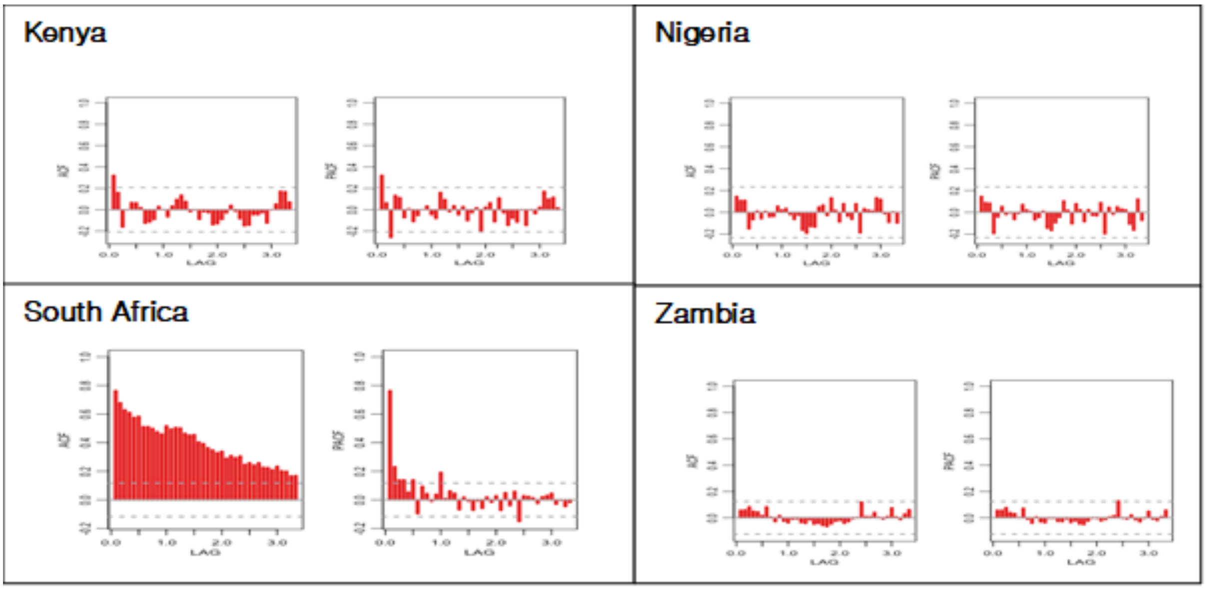
Table 3.4b: FPEO Descriptive Statistics, Sub - Samples

Description	Kenya	Nigeria	South Africa		Zambia	
	After	After	Before	After	Before	After
Mean*	92.00005	140.7022	1,752.087	6,017.495	478.2712	2,406.667
Median*	85.06287	127.2321	1,662.095	5,865.910	33.30274	854.9865
Maximum*	180.7379	426.9958	5,109.430	11,061.50	10,848.58	85,194.11
Minimum*	44.42177	25.78277	379.0300	3,342.060	1.027000	1.469000
Standard Deviation	29.68098	80.47882	972.4190	1,311.561	1,546.825	8,085.506
Skewness	0.984948	1.393117	0.920576	1.183666	4.815967	8.408792
Kurtosis	3.778416	5.523909	3.972185	5.263153	27.44682	81.45285
Jarque-Bera (JB)	13.64620	27.67754	26.00991	65.69747	3,394.571	38,089.61
Probability	0.001088	0.000001	0.000002	0.000000	0.000000	0.000000
Observations	73	47	144	147	118	142

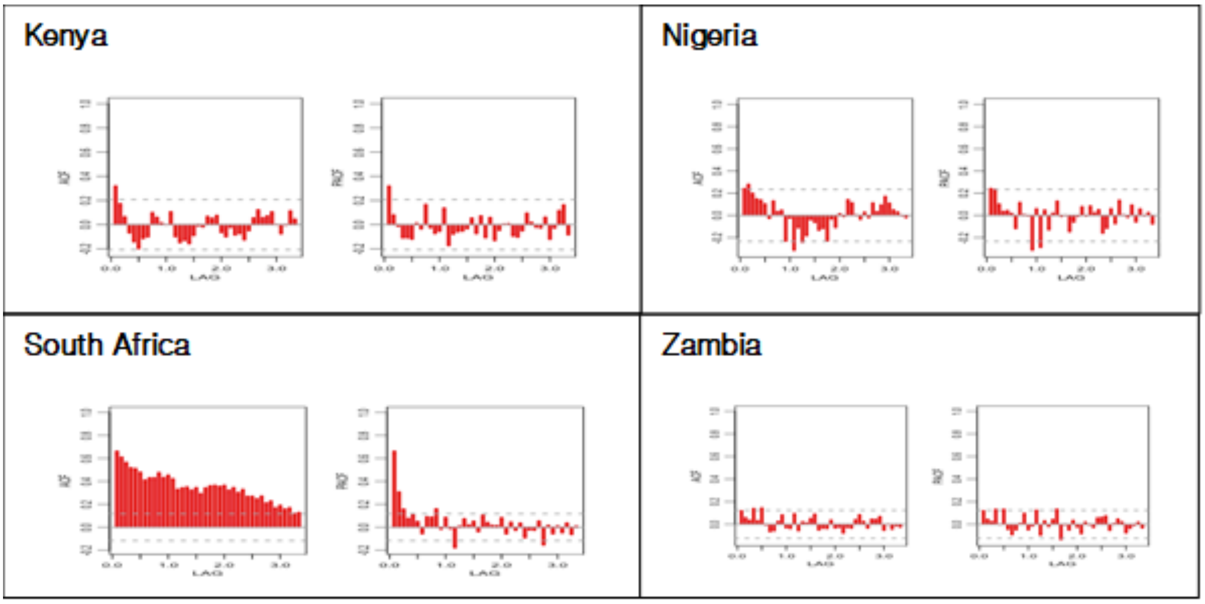
* Values are in millions of US Dollars save for Zambia whose values are in thousands of US dollars.
Source: Author, EViews output.

3.3.4. Autocorrelation Functions

The Autocorrelations Functions (ACF) and Partial Autocorrelation Functions (PACF) suggest that data for all the countries except South Africa is stationary, as their respective ACF and PACF for both the inflows and outflows lie within the bounds (Figure 3.3).



Source: Author, Studio R urca - source:(ac.R) - Package Output.
Figure 3.3a: ACF and PACF – Inflows Full Sample.



Source: Author, Studio R urca - source:(ac.R) - Package Output.
Figure 3.3b: ACF and PACF – Outflows Full Sample.

This suggests that each series, except for South Africa, could be of short-range dependence. The South Africa's inflows and outflows show slowly decaying ACF, suggesting its series may be fractionally integrated (i.e. not being of integer order of integration) and probably have long-range or short-range dependence. This means that other statistical tools capable of dealing with data that has fractal properties are needed to establish the true underlying process of the gross foreign portfolio equity flows linked to South Africa.

3.3.5. Unit Root Tests

The unit root tests suggest that foreign portfolio equity inflows (full sample) for Kenya and Nigeria are integrated of mixed order (Table 3.5a). The Augmented Dickey-Fuller (ADF) test statistic under the assumption of constant and linear trend (the assumption adopted for all the unit root tests undertaken in this study) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test statistic, suggest inflows to Kenya are integrated of order one (i.e. being I(1) series). This means that the series is not stationary as it seems to have a unit root, implying the series need to be differenced once to render it stationary. Thus, the Kenyan series is the first difference stationary type. Similarly, the ADF and the Zivot-Andrews (ZA) tests indicate that Nigeria's inflows are also an I(1) series. However, the Phillips-Perron (PP) test statistic and the ZA test for Kenya's data, and the KPSS as well as the PP tests for Nigeria's data, show that the series for each of the two countries is stationary given their orders of integration of zero (i.e. being I(0) series). These mixed results make the two series to be of mixed order of integration.

Table 3.5a: Unit Root Test Results for Foreign Portfolio Equity Inflows – Full Sample

Country	Method	Test Statistic	P-Value	First/Second Difference Test statistic	P-Value	Integration Order	Z-A test Structural Break Date
Kenya	ADF	-3.037312	0.1280	-15.50108	0.0000	I(1)	
	KPSS	0.278225		0.036817		I(1)	
	PP	-5.022127	0.0004			I(0)	
	ZA	-5.502086	0.00718			I(0)	Nov. 2015
Nigeria	ADF	-2.629140	0.2691	-10.93549	0.0000	I(1)	
	KPSS	0.120767				I(0)	
	PP	-6.250944	0.0000			I(0)	
	ZA	-3.892018	0.00018	-11.43564	0.01001	I(1)	May 2017
South Africa	ADF	-3.738175	0.0214			I(0)	
	KPSS	0.180638				I(0)	
	PP	-6.483870	0.0000			I(0)	
	ZA	-5.459021	0.00144			I(0)	Jun. 2005
Zambia	ADF	-15.36446	0.0000			I(0)	
	KPSS	0.058729				I(0)	
	PP	-15.45009	0.0000			I(0)	
	ZA	-15.64467	0.04506			I(0)	Aug. 2011

Critical values:

ADF-Constant & trend: Kenya- 1% level (-4.062040), 5% level (-3.459950), 10% level (-3.156109)
ADF-Constant & trend: Nigeria- 1% level (-4.094550), 5% level (-3. 475305), 10% level (-3.165046)
ADF-Constant & trend: RSA- 1% level (-3. 990131), 5% level (-3.425451), 10% level (-3.135864)
ADF-Constant & trend: Zambia- 1% level (-3. 993746), 5% level (-3.427203), 10% level (-3.136898)
KPSS - Constant & trend - 1% level (0.216000), 5% level (0.146000), 10% level (0.119000)
PP - Constant & trend - 1% level (0.739000), 5% level (0.463000), 10% level (0.347000)
ZA-Constant & trend - 1% (-5.57), 5% (-5.08), 10% (-4.82)

Source: Author, EViews output based on data from CMA, NgSE, SARB and BoZ.

However, all four unit root test statistics in respect of South Africa and Zambia's foreign portfolio equity inflows indicate that the two series are I(0) processes, meaning that they are stationary, even in the presence of structural breaks as revealed by the ZA algorithm. A stationary process is also suggested for Kenya, South Africa and Zambia's series falling under the period after the respective countries identified structural breaks, being *SA_Fepi_Jan2006StrBrk*, *Kn_Fepi_Aug2012StrBrk* and *Zm_Fepi_Jan2006StrBrk (*Table 3.5b*).*

Table 3.5b: Unit Root Test for Foreign Portfolio Equity Inflows-After Structural Break

Country	Method	Test Statistic	P-Value	First/Second Difference Test statistic	P-Value	Integration Order
Kenya	ADF	-3.909672	0.0164			I(0)
	KPSS	0.131944				I(0)
	PP	-5.997192	0.0000			I(0)
South Africa	ADF	-6.154085	0.0000			I(0)
	KPSS	0.164973				I(0)
	PP	-6.328644	0.0000			I(0)
Zambia	ADF	-12.02353	0.0000			I(0)
	KPSS	0.053819				I(0)
	PP	-12.06161	0.0000			I(0)

Critical values:

ADF-Constant & trend: Kenya- 1% level (-4.088713), 5% level (-3.472558), 10% level (-3.163450)

ADF-Constant & trend: RSA- 1% level (-4.021691), 5% level (-3.440681), 10% level (-3.144830)

ADF-Constant & trend: Zambia- 1% level (-4.019561), 5% level (-3.439658), 10% level (-3.144229)

KPSS - Constant & trend - 1% level (0.216000), 5% level (0.146000), 10% level (0.119000)

PP - Constant & trend - 1% level (0.739000), 5% level (0.463000), 10% level (0.347000)

ZA-Constant & trend - 1% (-5.57), 5% (-5.08), 10% (-4.82)

Source: Author, EViews output based on data from CMA, NgSE, SARB and BoZ.

Contrary to the mixed order of integration in respect of the inflows, foreign portfolio equity outflows are all I(0) processes (i.e. stationary in levels) for all four countries, even in the presence of structural breaks in each series as suggested by the ZA tests (Table 3.6a). Also, when the structural breaks *SA_Fepo_Jan2006StrBrk*, *Kn_Fepo_Jan2013StrBrk*, *Ng_Fepo_Apr2015StrBrk*, and *Zm_Fepo_Nov2006StrBrk* are taken into account, the series after these breaks are stationary, thus being I(0) processes, for all the four countries (Table 3.6b). This implies that in all the four countries, effects of shocks to the foreign portfolio equity outflows are non-persistent.

Table 3.6a: Unit Root Test Results for Foreign Portfolio Equity Outflows – Full Sample

Country	Method	Test Statistic	P-Value	First/Second Difference Test statistic	P-Value	Integration Order	Z-A test Structural Break Date
Kenya	ADF	-6.24160	0.0000	-	-	I(0)	
	KPSS	0.17285		-	-	I(0)	
	PP	-6.43899	0.0000	-	-	I(0)	
	ZA	-5.49646	0.00173	-	-	I(0)	Sep. 2015
Nigeria	ADF	-4.71641	0.0015	-	-	I(0)	
	KPSS	0.156875		-	-	I(0)	
	PP	-4.68581	0.0017	-	-	I(0)	
	ZA	-6.37952	0.00103	-	-	I(0)	Dec 2014
South Africa	ADF	-4.17354	0.0055	-	-	I(0)	
	KPSS	0.15176		-	-	I(0)	
	PP	-9.55841	0.0000	-	-	I(0)	
	ZA	-5.32404	0.00127	-	-	I(0)	Aug. 2005
Zambia	ADF	-15.9489	0.0000	-	-	I(0)	
	KPSS	0.08653		-	-	I(0)	
	PP	-15.9489	0.0000	-	-	I(0)	
	ZA	-16.2421	0.05421	-	-	I(0)	Apr. 2011

Critical values:

ADF-Constant & trend: Kenya- 1% level (-4.060874), 5% level (-3. 459397), 10% level (-3.155786)
ADF-Constant & trend: Nigeria- 1% level (-4.090602), 5% level (-3.473447), 10% level (-3.163967)
ADF-Constant & trend: RSA- 1% level (-3. 990131), 5% level (-3. 425451), 10% level (-3.135864)
ADF-Constant & trend: Zambia- 1% level (-3.993746), 5% level (-3. 427203), 10% level (-3.136898)
KPSS - Constant & trend - 1% level (0.216000), 5% level (0.146000), 10% level (0.119000)
PP - Constant & trend - 1% level (0.739000), 5% level (0.463000), 10% level (0.347000)
ZA-Constant & trend - 1% (-5.57), 5% (-5.08), 10% (-4.82)

Source: Author, EViews output based on data from CMA, NgSE, SARB and BoZ.

Table 3.6b: Unit Root Test for Foreign Portfolio Equity Outflows – Post Structural Break

Country	Method	Test Statistic	P-Value	First/Second Difference Test statistic	P-Value	Integration Order
Kenya	ADF	-6.287538	0.0000	-	-	I(0)
	KPSS	0.069895		-	-	I(0)
	PP	-6.419321	0.0000	-	-	I(0)
Nigeria	ADF	-5.494327	0.0002	-	-	I(0)
	KPSS	0.149708		-	-	I(0)
	PP	-5.550804	0.0002	-	-	I(0)
South Africa	ADF	-5.336391	0.0001	-	-	I(0)
	KPSS	0.160934		-	-	I(0)
	PP	-8.491476	0.0000	-	-	I(0)
Zambia	ADF	-11.97342	0.0000	-	-	I(0)
	KPSS	0.067899		-	-	I(0)
	PP	-11.97345		-	-	I(0)

Critical values:

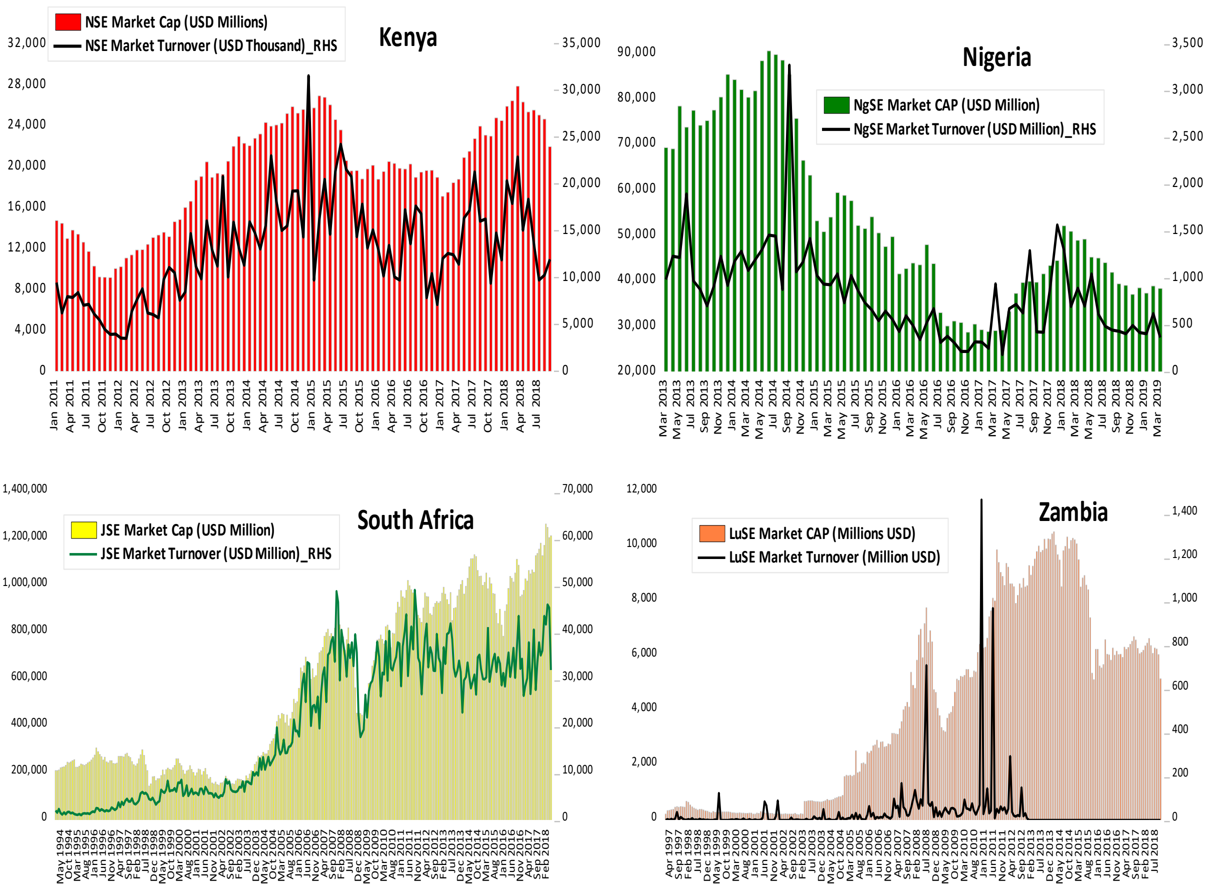
ADF-Constant & trend: Kenya- 1% level (-4.098741), 5% level (-3.477275), 10% level (-3.1661909)
ADF-Constant & trend: Nigeria- 1% level (-4.165756), 5% level (-3.508508), 10% level (-3.184230)
ADF-Constant & trend: RSA- 1% level (-4.021691), 5% level (-3. 440681), 10% level (-3.144830)
ADF-Constant & trend: Zambia- 1% level (-4.023975), 5% level (-3.441777), 10% level (-3.145474)
KPSS - Constant & trend - 1% level (0.216000), 5% level (0.146000), 10% level (0.119000)
PP - Constant & trend - 1% level (0.739000), 5% level (0.463000), 10% level (0.347000)
ZA-Constant & trend - 1% (-5.57), 5% (-5.08), 10% (-4.82)

Source: Author, EViews output based on data from CMA, NgSE, SARB and BoZ.

3.4. Stock Market Data

3.4.1. Trending Behaviour

While market capitalisation for the JSE and Kenya's NSE have largely increased over the respective sample periods, this has not been the case for Nigeria's NgSE and Zambia's LuSE, as the two have had mixed outcomes over their respective sample periods (Figure 3.4). Market capitalisation for the two latter countries' stock exchanges remained below their 2014 peaks towards the end of their respective samples, partly owing to the slowdown in economic activity after the 2015 commodity price collapse (oil for Nigeria and copper for Zambia). The commodity price decline follows the shock induced by the US FRB's decision to end the UMP. Nigeria's decline in economic activity during the period is very apparent, as shown in Figure 3.5c in the section that follows. For Zambia, a huge fiscal deficit may have also contributed to the subdued stock market activities, as this has had a toll on liquidity in the economy. This follows government recourse to domestic financing of its fiscal deficit and build up in its domestic debt arrears since 2015.



Source: CMA, NgSE, SARB and BoZ.

Figure 3.4: Stock Market Indicators

With the exception of the LuSE, market turnover for the other three exchanges largely tracked market capitalisation. The market turnover series for LuSE displays a huge spike around November 2010 owing to the Bharti Airtel MO transaction mentioned previously, but otherwise broadly remained very low, with a median monthly transaction value of US $2.96 million, and averaging US $32 million per month (Table 3.7b) in the period after the biggest spike in the series.

3.4.2. Descriptive Statistics

South Africa's market capitalisation is the largest among the four countries, with a maximum value of US $1.3 trillion and a minimum of US $146 billion over the sample period (Table 3.5a). Zambia is the sample country with the smallest market capitalisation, recording a maximum of US $10.6 billion over the sample period, while Nigeria and Kenya's market capitalisations are all several billion US dollar more than Zambia's over the sample period, and thus far larger than Zambia's.

Only Kenya's market capitalisation is negatively skewed, but one of the four series are normally distributed based on their kurtosis and JB statistics. Similarly, market turnover is larger for South Africa's JSE, averaging US $20 billion per month, with the highest market turnover of US $49.1 billion (Table 3.7b). In all the four countries, as indicated by the JB statistics and levels of the kurtosis, market turnover is positively skewed and not normally distributed.

Table 3.7a: Market Capitalisation Descriptive Statistics

Description	Kenya	Nigeria	South Africa	Zambia
Mean*	19,480.32	53,330.94	571,686.00	4,134.95
Median*	19,753.82	48,751.84	472,476.00	3,902.00
Maximum*	27,844.75	90,366.59	1,265,497.00	10,561.00
Minimum*	9,123.895	28,563.70	146,816.00	215.00
Standard Deviation	5109.227	18750.31	0.347107	3.460241
Skewness	-0.429457	0.565795	0.251962	0.306394
Kurtosis	2.107794	2.030857	1.465328	1.687194
Jarque-Bera (JB)	5.943338	6.751687	31.74475	22.82630
Probability	0.051218	0.034189	0.000000	0.000011
Observations	93	73	292	261

* Values are in millions of US Dollar.
Source: Author, EViews output based on data from CMA, NgSE, SARB and BoZ.

Table 3.7b: Market Turnover Descriptive Statistics

Description	Kenya	Nigeria	South Africa	Zambia
Mean*	1,295.117	814.9838	20,039.96	32.16724
Median*	1,299.900	713.6111	19,716.10	2.963476
Maximum*	3,158.300	3,270.079	49,149.09	1,466.328
Minimum*	349.3000	178.9474	1,077.090	0.001573
Standard Deviation	539.5132	477.9662	14447.97	121.2653
Skewness	0.497695	2.001327	0.095270	8.926269
Kurtosis	3.296361	10.79509	1.445609	93.28714
Jarque-Bera (JB)	4.179691	233.5533	29.83797	92116.48
Probability	0.123706	0.000000	0.000000	0.000000
Observations	93	73	292	261

* Values are in millions of US Dollar.
Source: Author, EViews output based on data from CMA, NgSE, SARB and BoZ.

3.4.3. Unit Root Tests

Whilst the stock market capitalisation variable is largely I(1) for South Africa, it is of mixed order of integration for the other three countries (see Table 3.8a).

Table 3.8a: Unit Root Test Results for Market Capitalisation

Country	Method	Test Statistic	P-Value	First/Second Difference Test statistic	P-Value	Integration Order
Kenya	ADF	-1.116056	0.9202	-7.120593	0.0000	I(1)
	KPSS	0.180288				I(0)
	PP	-1.565177	0.7991	-7.270283	0.0000	I(1)
	ZA	-4.097098	0.000689			I(0)
Nigeria	ADF	-1.775361	0.7063	-6.575316	0.0000	I(1)
	KPSS	0.183024				I(0)
	PP	-1.731167	0.7272	-6.596723	0.0000	I(1)
	ZA	-3.767776	0.046219			I(0)
South Africa	ADF	-2.380062	0.3892	-15.45361	0.0000	I(1)
	KPSS	0.238829		0.040307		I(1)
	PP	-2.497170	0.3294	-15.45769	0.0000	I(1)
	ZA	-4.457192	0.007409			I(0)
Zambia	ADF	-1.148240	0.9177	-16.19876	0.0000	I(1)
	KPSS	0.209526				I(0)
	PP	-1.342885	0.8748	-16.24217	0.0000	I(1)
	ZA	-3.718171	0.003055			I(0)

Critical values:
ADF-Constant & trend: Kenya- 1% level (-4.060874), 5% level (-3.459397), 10% level (-3.155786)
ADF-Constant & trend: Nigeria- 1% level (-4.092547), 5% level (-3.474363), 10% level (-3.164499)
ADF-Constant & trend: RSA- 1% level (-3.989908), 5% level (-3.425343), 10% level (-3.135800)
ADF-Constant & trend: Zambia- 1% level (-3.993746), 5% level (-3.427203), 10% level (-3.136898)
KPSS - Constant & trend - 1% level (0.216000), 5% level (0.146000), 10% level (0.119000)
PP - Constant & trend - 1% level (0.739000), 5% level (0.463000), 10% level (0.347000)
ZA-Constant & trend - 1% (-5.57), 5% (-5.08), 10% (-4.82)

Source: Author, EViews output based on data from CMA, NgSE, SARB and BoZ.

However, stock market turnover variables have mixed test results for all four countries. The market turnover series for Kenya and South Africa are largely of I(1) order of integration (first difference stationary), based on the results from three of the four test methods (Table 3.8b). Similarly, the series for Nigeria and Zambia are of mixed order of integration but specifically for Zambia, the KPSS test statistic suggests that its market turnover is integrated of the second order, i.e. it is an I(2) series, meaning the series has to be differenced twice for it to become stationary.

Table 3.8b: Unit Root Test Results for Market Turnover

Country	Method	Test Statistic	P-Value	First/Second Difference Test statistic	P-Value	Integration Order
Kenya	ADF	-3.085909	0.1159	-10.74732	0.0000	I(1)
	KPSS	0.242464		0.029111		I(1)
	PP	-6.149081	0.0000			I(0)
	ZA	-4.787870	0.000006			I(1)
Nigeria	ADF	-2.606287	0.2790	-10.46275	0.0000	I(1)
	KPSS	0.130220				I(0)
	PP	-6.795865	0.0000			I(0)
	ZA	-3.630233	0.001419			I(1)
South Africa	ADF	-2.105266	0.5402	-5.714102	0.0000	I(1)
	KPSS	0.220239		0.156839		I(1)
	PP	-6.109363	0.0000			I(0)
	ZA	-5.917956	0.00009			I(0)
Zambia	ADF	-3.403464	0.0531			I(0)
	KPSS	0.297696		0.028755		I(2)
	PP	-14.71966	0.0000			I(0)
	ZA	-9.182326	0.000763			I(0)

Critical values:

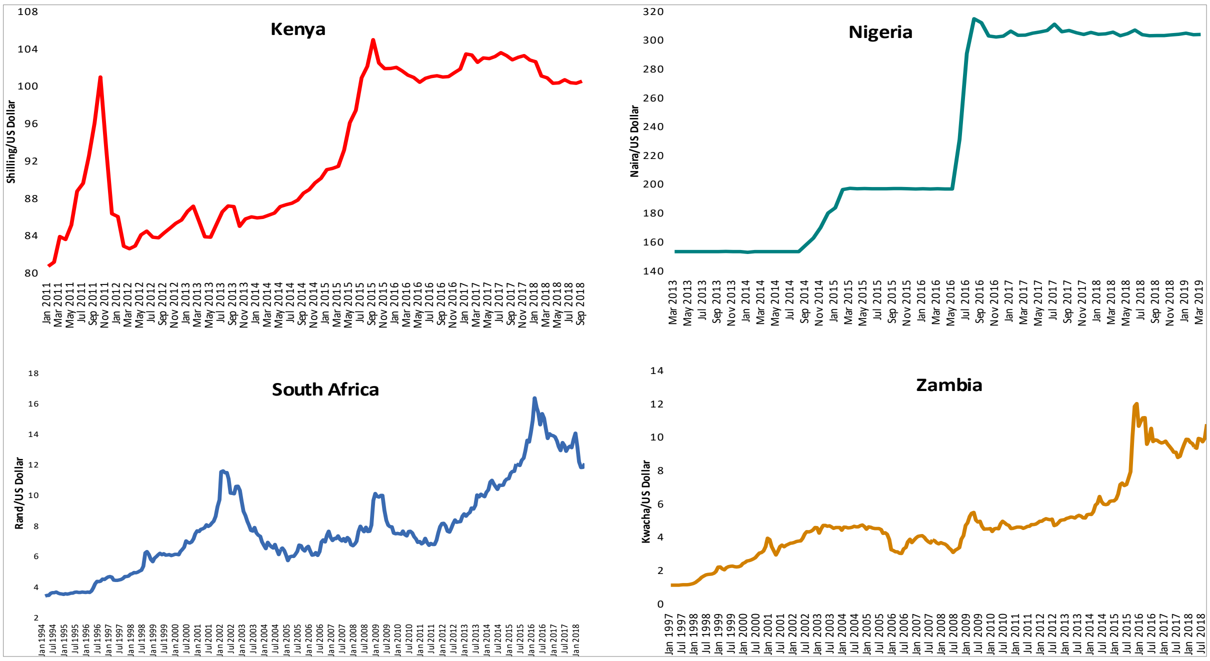
ADF-Constant & trend: Kenya- 1% level (-4.062040), 5% level (-3. 459950), 10% level (-3. 156109)
ADF-Constant & trend: Nigeria- 1% level (-4. 094550), 5% level (-3. 475305), 10% level (-3.165046)
ADF-Constant & trend: RSA- 1% level (-3. 991292), 5% level (-3. 426014), 10% level (-3. 136196)
ADF-Constant & trend: Zambia- 1% level (-3.994453), 5% level (-3.427546), 10% level (-3.137100)
KPSS - Constant & trend - 1% level (0.216000), 5% level (0.146000), 10% level (0.119000)
PP - Constant & trend - 1% level (0.739000), 5% level (0.463000), 10% level (0.347000)
ZA-Constant & trend - 1% (-5.57), 5% (-5.08), 10% (-4.82)

Source: Author, EViews output based on data from CMA, NgSE, SARB and BoZ.

3.5. Macroeconomic Variables Data

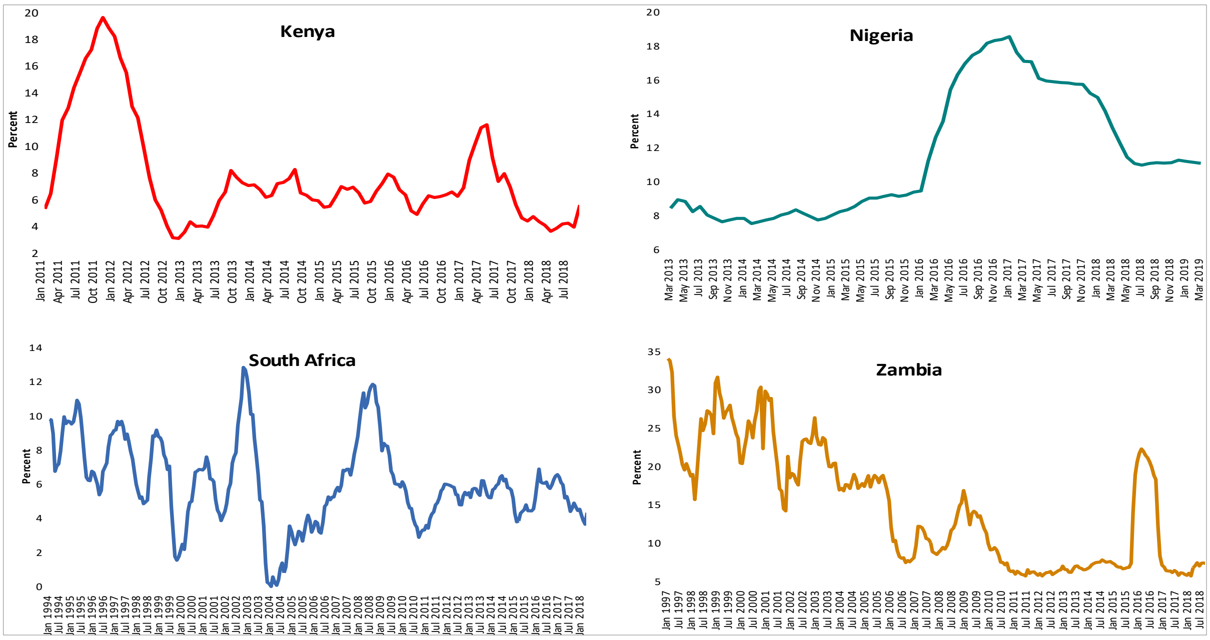
3.5.1. Trending Behaviour

Whilst the exchange rate of each country's currency against the US dollar has trended upward for the four SSA countries under investigation, signifying depreciation over time (Figure 3.5a), headline inflation generally trended downward over the same sample periods for each country (Figure 3.5b). However, periods of marked exchange rate depreciations coincided with a rise in inflation for each country, suggesting adverse pass-through effects of exchange rate depreciation to inflation. Real economic activity (RPSC or PVMP) for all the countries, except Nigeria, shows a rising trajectory over the respective sample periods (Figure 3.5c). Nigeria's decline in RPSC coincides with the time of recession the country experienced after the 2015/2016 oil (commodity) price decline following the end to the FRB's UMP, as stated before.



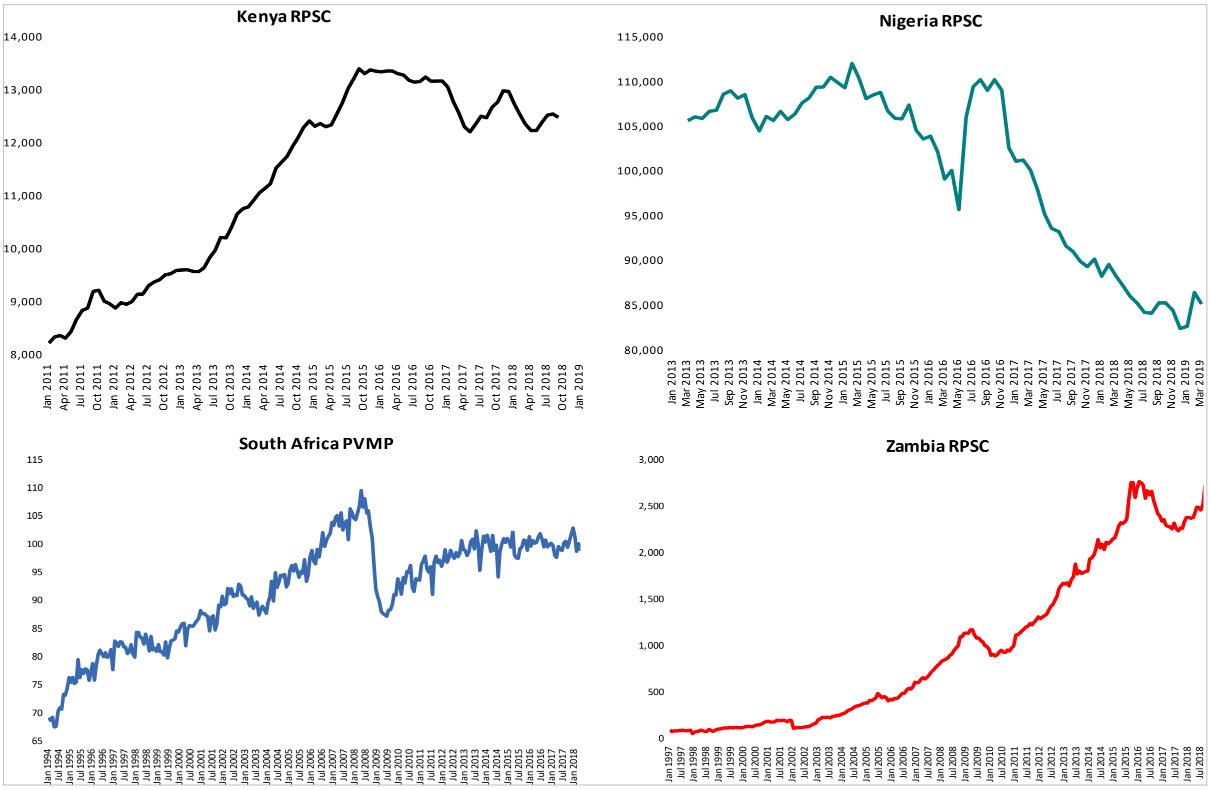
Source: CBK, CBN, SARB and BoZ.

Figure 3.5a: Macroeconomic Variables – Exchange Rates



Source: KNBS, NBS, SSA and ZamStat.

Figure 3.5b: Macroeconomic Variables – Inflation



Source: SARB and author using data from CBK, CBN, KNBS, NBS, SSA, BoZ, SARB and ZamStat.

Figure 3.5c: Macroeconomic Variables - Proxy for Real Economic Activity

3.5.2. Descriptive Statistics

The data for the dollar to local currency exchange rates for Kenya and Nigeria are symmetrically distributed, with a skewness close to zero. In contrast Zambia and South Africa's exchange rate data are non-symmetrically distributed, with skewness being in the neighbourhood of 1.0. (Table 3.9a).

Table 3.9a: Descriptive Statistics for USD Exchange Rate

Description	Kenya	Nigeria	South Africa	Zambia
Mean	93.71699	235.5478	7.919775	5.024674
Median	91.73000	198.9559	7.371796	4.710000
Maximum	105.2800	316.8261	16.38007	12.18000
Minimum	81.03000	154.7343	3.409312	1.290000
Standard Deviation	7.912102	67.24693	2.944751	2.439716
Skewness	0.015696	0.025497	0.674520	1.008755
Kurtosis	1.280850	1.190251	2.895401	3.553247
Jarque-Bera (JB)	11.45629	9.969947	22.27535	47.59367
Probability	0.003253	0.006840	0.000015	0.000000
Observations	93	73	292	261

Source: Author, EViews computations based on data from CBK, CBN, SARB and BoZ.

However, all four series are right skewed and consequently appear to be non-normally distributed, as evidenced by their kurtosis and JB statistics. Nigeria's exchange rate data is more variable (*i.e.* has a relatively high standard deviation), largely influenced by the level shift in the series around the middle period of 2016. This followed a devaluation of the exchange rate in mid-2016 as a policy response to deal with the imbalances in the economy following the fall in oil prices (Ewa, Adebisi, and Ijing, 2018; and IMF, 2016a). Zambia's exchange rate averaged 5.02 Kwacha/USD, while that of South Africa averaged 7.92 Rand/USD. The Kenyan Shilling averaged 93.72/ USD over the sample period, with Nigeria's Naira averaging 235.55/USD.

With regards to inflation, Zambia's average annual inflation rate of 15.0 percent over the period is the highest among the four countries in the study (Table 3.9b), followed by Nigeria (11.7 percent), Kenya (7.8 percent) and South Africa (6.2 percent), respectively. All four inflation data series are right skewed and non-normally distributed.

Table 3.9b: Descriptive Statistics for Headline Inflation

Description	Kenya	Nigeria	South Africa	Zambia
Mean	7.794409	11.70233	6.203280	14.96892
Median	6.620000	11.23000	6.002330	13.75789
Maximum	19.72000	18.72000	13.00659	34.42094
Minimum	3.200000	7.700000	0.164486	6.081242
Standard Deviation	3.916331	3.660253	2.505757	7.738420
Skewness	1.557293	0.585288	0.217760	0.481157
Kurtosis	4.662934	1.828924	3.091690	1.990207
Jarque-Bera (JB)	48.30574	8.339229	2.410032	21.15983
Probability	0.000000	0.015458	0.299687	0.000025
Observations	93	73	292	261

Source: Author, EViews computations based on data from KNBS, NBS, SSA and ZamStat.

The proxy for economic activity for Kenya, Nigeria and South Africa are negatively skewed (Table 3.9c). However, all the four countries data are not normally distributed, as evidenced by the JB statistic and kurtosis that is not equal to 3.0.

Table 3.9c: Descriptive Statistics for Economic Activity' Proxy Variables

Description	Kenya	Nigeria	South Africa	Zambia
Mean	11356.13	100720.0	92.10219	1011.710
Median	12262.32	105967.4	93.73500	809.6027
Maximum	13453.99	112358.4	109.8600	2784.395
Minimum	8277.374	82703.25	67.88000	76.37790
Standard Deviation	1719.034	9339.792	9.122119	866.4968
Skewness	-0.368780	-0.658875	-0.509755	0.635298
Kurtosis	1.559574	1.869862	2.448832	1.990427
Jarque-Bera (JB)	10.14794	9.166607	16.34211	28.64096
Probability	0.006258	0.010221	0.000283	0.000001
Observations	93	73	292	261

Source: Author, EViews computations based on data from CBK, CBN, KNBS, NBS, SSA, BoZ, SARB and ZamStat.

3.5.3. Unit Root Tests

The test statistics indicate that Nigeria exchange rate is the only one that has a mixed order of integration, with the ADF and the PP suggesting the series to be integrated of order one and thus having a unit root (see Table 3.10a). However, the KPSS shows the exchange rates in the four countries to be stationary. The ZA does not reject the hypothesis of the presence of the unit root, with structural breaks in both the constant and the trend for Kenya, South Africa and Zambia.

Table 3.10a: Unit Root Test Results for the Exchange Rates

Country	Method	Test Statistic	P-Value	First/Second Difference Test statistic	P-Value	Integration Order
Kenya	ADF	-2.38559	0.3845	-5.963696	0.0000	I(1)
	KPSS	0.145245				I(0)
	PP	-2.213714	0.4762	-6.83678	0.0000	I(1)
	ZA	-4.564992	0.000445			I(1)
Nigeria	ADF	-1.742218	0.7218	-5.953938	0.0000	I(1)
	KPSS	0.118660				I(0)
	PP	-1.87073	0.6593	-3.475726	0.0498	I(1)
	ZA	-10.34815	0.00000			I(0)
South Africa	ADF	-2.292011	0.4365	-12.40717	0.0000	I(1)
	KPSS	0.189023				I(0)
	PP	-2.09578	0.5455	-12.3806	0.0000	I(1)
	ZA	-4.149162	0.000489			I(1)
Zambia	ADF	-1.527705	0.8178	-11.73359	0.0000	I(1)
	KPSS	0.279804		0.060659		I(1)
	PP	-1.776902	0.7133	-11.54853	0.0000	I(1)
	ZA	-4.725488	0.00002			I(1)

Critical values:

ADF-Constant & trend: Kenya- 1% level (-4.063233), 5% level (-3.460516), 10% level (-3.156439)
ADF-Constant & trend: Nigeria- 1% level (-4.09455), 5% level (-3.475305), 10% level (-3.165046)
ADF-Constant & trend: RSA- 1% level (-3.990019), 5% level (-3.425397), 10% level (-3.135832)
ADF-Constant & trend: Zambia- 1% level (-3.994026), 5% level (-3.427339), 10% level (-3.136978)
KPSS - Constant & trend - 1% level (0.216000), 5% level (0.146000), 10% level (0.119000)
PP - Constant & trend - 1% level (0.739000), 5% level (0.463000), 10% level (0.347000)
ZA-Constant & trend - 1% (-5.57), 5% (-5.08), 10% (-4.82)

Source: Author, EViews output based on data from CBK, CBN, BoZ, and SARB.

For headline inflation, according to the ADF Nigeria's series is integrated of order 2, thus being second difference stationary (Table 3.10b). This means it has two unit roots and requires to be differenced twice to be stationary. However, South Africa's inflation is largely stationary, as suggested by three of the four tests methods, while Kenya and Zambia's headline inflation are largely I(1) type of series, and may have structural breaks in their series given the ZA test results. The proxies for economic activity are largely first difference stationary, i.e. being I(1) series (Table 3.10c).

Table 3.10b: Unit Root Test Results for Headline Inflation

Country	Method	Test Statistic	P-Value	First/Second Difference Test statistic	P-Value	Integration Order
Kenya	ADF	-2.980420	0.1434	-4.581616	0.0020	I(1)
	KPSS	0.108195				I(0)
	PP	-2.819707	0.1942	-4.492116	0.0027	I(1)
	ZA	-5.124909	0.103860			I(1)
Nigeria	ADF	-1.245239	0.8926	-4.086320	0.0104	I(2)
	KPSS	0.169784				I(0)
	PP	-1.063189	0.9277	-4.034905	0.0118	I(1)
	ZA	-6.907938	0.0000001			I(0)
South Africa	ADF	-2.699162	0.2378	-7.311591	0.0000	I(1)
	KPSS	0.084297				I(0)
	PP	-3.657339	0.0269			I(0)
	ZA	-5.207449	0.020400			I(0)
Zambia	ADF	-2.041325	0.5754	-8.286576	0.0000	I(1)
	KPSS	0.246482		0.024367		I(1)
	PP	-3.574230	0.0340			I(0)
	ZA	-4.904512	0.000784			I(1)

Critical values:

ADF-Constant & trend: Kenya- 1% level (-4.062040), 5% level (-3.459950), 10% level (-3.156109)
ADF-Constant & trend: Nigeria- 1% level (-4.098741), 5% level (-3.477275), 10% level (-3.166190)
ADF-Constant & trend: RSA- 1% level (-3.990019), 5% level (-3.426073), 10% level (-3.136231)
ADF-Constant & trend: Zambia- 1% level (-3.995492), 5% level (-3.428049), 10% level (-3.137397)
KPSS - Constant & trend - 1% level (0.216000), 5% level (0.146000), 10% level (0.119000)
PP - Constant & trend - 1% level (0.739000), 5% level (0.463000), 10% level (0.347000)
ZA-Constant & trend - 1% (-5.57), 5% (-5.08), 10% (-4.82)

Source: Author, EViews output based on data from KNBS, NBS, SSA and ZamStat.

Table 3.10c: Unit Root Test Results for Proxy for Economic Activity

Country	Method	Test Statistic	P-Value	First/Second Difference Test statistic	P-Value	Integration Order
Kenya	ADF	-0.611126	0.9758	-5.554361	0.0001	I(1)
	KPSS	0.253987		0.129255		I(1)
	PP	-0.348595	0.9880	-5.583248	0.0001	I(1)
	ZA	-4.041674	0.007974			I(1)
Nigeria	ADF	-2.170036	0.4985	-8.217458	0.0000	I(1)
	KPSS	0.231648		0.052698		I(1)
	PP	-2.194218	0.4853	-8.217496	0.0000	I(1)
	ZA	-3.457312	0.002314			I(1)
South Africa	ADF	-2.676752	0.2471	-23.77316	0.0000	I(1)
	KPSS	0.301992		0.027064		I(1)
	PP	-3.153568	0.0961			I(0)
	ZA	-6.187308	0.0000			I(0)
Zambia	ADF	-2.210132	0.4815	-4.219287	0.0048	I(1)
	KPSS	0.405462		0.046212		I(1)
	PP	-1.909475	0.6467	-14.41396	0.0000	I(1)
	ZA	-3.117564	0.021999			I(1)

Critical values:

ADF-Constant & trend: Kenya- 1% level (-4.062040), 5% level (-3.459950), 10% level (-3.156109)
ADF-Constant & trend: Nigeria- 1% level (-4.090602), 5% level (-3.473447), 10% level (-3.163967)
ADF-Constant & trend: RSA- 1% level (-3.990019), 5% level (-3.425397), 10% level (-3.135832)
ADF-Constant & trend: Zambia- 1% level (-3.994453), 5% level (-3.427546), 10% level (-3.137100)
KPSS - Constant & trend - 1% level (0.216000), 5% level (0.146000), 10% level (0.119000)
PP - Constant & trend - 1% level (0.739000), 5% level (0.463000), 10% level (0.347000)
ZA-Constant & trend - 1% (-5.57), 5% (-5.08), 10% (-4.82)

Source: Author, EViews output based on data from CBK, CBN, KNBS, NBS, SSA, BoZ, SARB and ZamStat.

3.6. Implications of the Descriptive and Test Statistics on Empirical Work

The descriptive statistics and test results obtained have implications on the choice of empirical method to use, either in the univariate or multivariate setup. As established in literature in Chapter 2, some univariate methods, especially related to the empirical analysis of the underlying process of foreign portfolio equity flows, the subject of Chapter 4 of this thesis, are sensitive to the stationarity (or lack thereof) in the data and this may need to be considered in the estimation procedure if realistic estimates are to be obtained. In this regard, an estimation method that can handle both stationary data and data with a trend would be suitable for this study, given the unit root test results. Further, a method that does not impose assumptions on the distribution of the data (*e.g.* does not assume data to be normally distributed) is required to deal with the data of the kind used for this study on the four SSA countries.

Equally, in a multivariate setup, such as the work undertaken in Chapter 5, which aims to establish the impact of gross foreign portfolio equity flows on stock market capitalisation, the order of integration of the data can be very important for optimal empirical analysis. This is because some multivariate methods, such as the vector autoregressive (VAR) method, are only good for stationary data (Pradhan and Bagchi, 2013). The other multivariate approach, the Vector Error Correction Mechanism (VECM) type of method requires that all the variables are I(1) in levels and cointegrated (see for example Pradhan and Bagchi, 2013; de Mello and Pisu, 2010; Obayelu and Salau, 2010; and Mahadevan and Asafu-Adjaye, 2007). However, for combined variables that are of mixed order of integration, the autoregressive lagged distributive models (ARDL) are ideal, as long as among the adopted variables none is an I(2) variable in the model being estimated (Nkoro and Uko, 2016; and Bildirici, 2013). Bayesian techniques, on the other hand, are ideal for data of mixed order of integration, whether with integer or fractional orders of integration (see, for example, Baillie, 1996). Based on the descriptive statistics and unit root tests described above, Bayesian techniques seem appropriate for the multivariate analysis in this study.

3.7. Chapter Summary

Except for Nigeria's FPEIs, which has no detected structural break, the series for the other countries, including the FPEOs, have multiple structural breaks. For each country, all the variables have different orders of integration – thus, some variables are I(0), others are I(1), some are I(2), and yet others do not have a conclusively determined order of integration (i.e. are of mixed order of integration). The descriptive statistics also largely show that most of the variables are not normally distributed.

Given the descriptive and mixed order of integration unit root test results, estimation methods that can handle both stationary data and data with a trend are optimal for this study. Also, a method that does not impose strict assumptions of normality on the estimation procedure will give better results, especially as the descriptive statistics show the data to be non-normal. Further, in view of the descriptive statistics and unit root test results, Bayesian techniques may be appropriate for the multivariate analysis in this study because the techniques are suitable for data with mixed order of integration, regardless of whether with integer or fractional order of integration.

The next chapter discusses the methodology and results of the exploration of the underlying process of the foreign portfolio equity flows conducted based on the estimated Hurst coefficient, as well as computing the correlation measure of these flows arising from the Hurst Coefficient.

Chapter 4
The Underlying Process of Foreign Portfolio Equity Flows: A Fractal Analysis

---

4.1. Introduction

In this chapter objectives 1 and 2 of this study are addressed through the estimation of the Hurst exponent (also referred to as Hurst coefficient or Hurst parameter), one of the measures of long-range or short-range dependence. The Hurst parameter is therefore estimated in respect of the foreign portfolio equity flows for four sub-Saharan Africa countries, namely Kenya, Nigeria, South Africa and Zambia. Specifically, the aim is to determine whether the underlying processes are random/independent, anti-persistent (stationary and mean reverting) or persistent (trend reinforcing). This is done using fractal analysis for computing the Hurst parameter, and thus satisfy objective 1 of the study. In addition, the determination of how the present (past) behaviour of foreign equity portfolio flows may impact on their future (current) behaviour is also undertaken based on the estimated Hurst parameter to address objective 2, and thereby further assist with the understanding of the nature of the underlying process of the gross foreign portfolio equity inflow and outflows for the four SSA countries.

4.2. Hurst Exponent Theoretical Framework: Fractional Brownian Motion Model

Fractional Brownian motion (fBm) is a valuable model in studies related to long-range and short range dependence (Shevchenko, 2015; Li, 2013; and Makarava, 2012). Such stochastic fractal processes are characterised by the Hurst parameter (Heneghan and McDarby, 2000), and the fBm offers valuable models for several natural time series (Mandelbrot and Van, 1968). The fBm process is regarded as a centered Gaussian process (Shevchenko, 2015) of the form:

$$B^H = \{B_t^H, t \geq 0\} \tag{4.1}$$

It has a covariance function of the type:

$$E[B_t^H B_s^H] = \frac{1}{2}(t^{2H} + s^{2H} - |t-s|^{2H}), s \geq 0 \quad (4.2)$$

where H is the Hurst parameter with limits $H \in [0,1]$. For the fBm to exist, the covariance function should be positive definite[49]. In addition, $H \neq 0.5$ must hold, otherwise it is a standard Weiner process (a strictly Brownian motion process). The difference between fBm and Brownian motion is related to the behaviour of successive increments. In fBm, successive increments are correlated with a positive correlation implying trend reinforcing properties, while a negative correlation indicates anti-persistence (Shevchenko, 2015 and Makarava, 2012).

The following are the characteristics of the fBm type of a process;

i. *Stationary increments:* The fBm process has stationary increments such that the incremental process of B^H is homogenous at any point.

ii. *Self-similarity:* The fBm process is said to be largely H-self-similar on account that $B_{\alpha t}^H$ is statistically equivalent to, say, $\alpha^H B_t^H$. This is because for a constant $\alpha > 0$ and $B_{\alpha t}^H, t \geq 0$ and $\alpha^H B_t^H, t \geq 0$, the two processes will have the same distribution (Shevchenko, 2015).

iii. *Long Range Dependency (LRD):* letting $cov[B_t^H B_s^H]$, for $t, s \in (-\infty, \infty)$, be the ACF of the fBm, following Heneghan and McDarby (2000) then;

$$cov[B_t^H B_s^H] = k(t^{2H} + s^{2H} - |t-s|^{2H}) \quad (4.3)$$

Where, k is a constant.

Following Li (2013) and Li and Zhao (2012), it follows that;

$$\int_{-\infty}^{\infty} E[B_t^H B_s^H]dt = \infty \quad (4.4)$$

This implies the function is non-integrable. The LRD (persistent behaviour) can be realised when $E[B_t^H B_s^H]$, for $t, s \in (0, \infty)$, takes the form;

[49] For proof, see Shevchenko (2015)

$$\int_0^\infty E[B_t^H B_s^H]dt = \infty, \qquad H \in (0.5, 1) \tag{4.5}$$

When $E[B_t^H B_s^H]$, for $t, s \in (0, \infty)$, and $H \in (0, 0.5)$ takes the form below, a short-range dependency (anti-persistence behaviour) is realised;

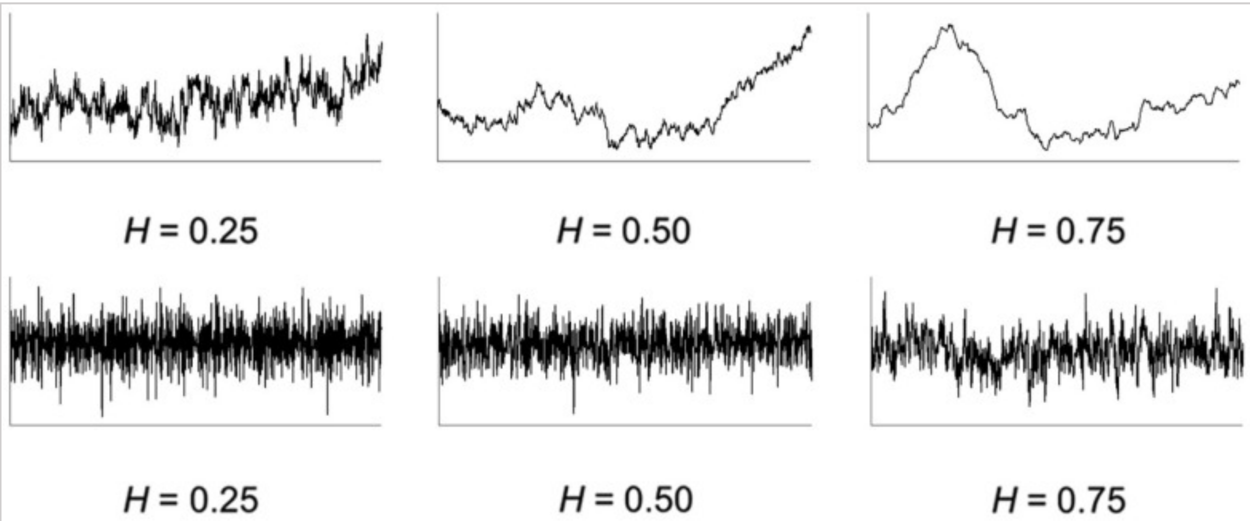
$$\int_0^\infty E[B_t^H B_s^H]dt < \infty, \tag{4.6}$$

It is important to highlight that signals with fractal properties exhibit power law of the type $1/f^{\beta}$ (Chen et al., 1997; and Pilgram and Kaplan, 1998). Consistent with this, Cannon *et al*. (1997), Eke *et al*. (2002) and Delignieres and Torre (2009) have submitted that the $1/f^{\beta}$ process can be contained in either of the fGn and fBm signals such that for $\beta \in (-1, 1)$, the fGn series is obtained, and for $\beta \in (1, 3)$, the fBm signal is realised (Serinaldi, 2010 and Cannon et al., 1997). In this regard, the fBm process is also necessary in the context of linking the power law exponent (β) and the *H* parameter. Power laws have influence on long-range dependency in the data through the ACF. According to Li and Zhao (2012), the ACF of the $1/f^{\beta}$ noise lies in the structure of the power function and follows power law.

It should be noted that White Gaussian noise is the underlying process of fGn type of the $1/f^{\beta}$ process with $\beta = 0$. The Brownian motion underpins the fBm process with $\beta = 2$ (Hausdorff et al., 2000), and a Brownian motion (Random Walk) with some compact form can be regarded to be a stationary process (Taleb, 2019). Both the fGn series and the fBm signal with $\beta < 2$ are regarded to be anti-persistent. Under this category, the fGn signal is stationary and so is the anti-persistent fBm, although this is within a relatively wider bounds than the case of the fGn signal. This then implies that the fBm signals can show persistence at local level yet be stationary at a global level within the defined bounds, which makes them anti-persistent, akin to mean reversion. The fBm signals of $\beta > 2$ are regarded to be persistent over a relatively longer period.

As highlighted in literature, both the fBm and fGn signals can have the same *H* parameter value. While the fGn and the anti-persistent fBm signals with the same *H* parameter value are both stationary processes, the fGn and the persistent fBm series with the same Hurst parameter value are fundamentally different as the latter is a trend reinforcing process.

To get a sense of the paths that the different class of the fBm and the fGn series can take under similar values of *H*, see Figure 4.1 below which depicts three typical example series of the fBm and the corresponding fGn series under the same *H* exponent value. The middle graph is a typical Brownian motion or random walk (H = 0.5). The graph on the top left side is an example of the anti-persistent fBm (H = 0.25), while the graph on the top right displays a typical persistent fBm (H = 0.75). The graphs in the bottom panel are the typical examples of the corresponding fGn signals for the similar Hurst parameter values.



Source: Marmelat et al. (2012).

Figure 4.1: fBm and fGn Signals' Evolution with Similar H Parameter Values

The visualisations above can assist with interpreting the results for the estimations involving the four countries under study in this research because they combine both the β and H values of a sequence of real numbers, as is the case with the gross foreign portfolio equity inflows and outflows time series data under consideration in this study.

4.3. The Methodology

This section explains the methodology used to investigate the signal classification and the underlying process of the FPEFs, and the estimation of the Hurst coefficient and the related correlation measure of these flows. Further, the method used for the estimation of the long-run (steady state) mean value of the flows, including the speed of adjustment of these flows to their steady state value, is also presented and discussed. This undertaking was necessary because the estimated underlying process of the fGn or an anti-persistent fBm signal are largely stationary and thus mean reverting. The estimations undertaken for each method described below considered each country's identified structural breaks[50] as described in Chapter 3.

4.3.1. Fractal Signal Classification: Power Spectral Density (PSD)(β)

In this study, the method implemented for computing β is the technique called lowPSD because it is ideal for both fBm and fGn type signals compared to alternative methods (see also Torre, Delignières and Lemoine, 2007; Delignieres *et al.* 2006: and Eke *et al.*, 2000, for a similar argument).

The procedure involves the following steps for a given series (signal) $y[n]$:

i) compute the mean

$$\bar{y} = n^{-1} \sum_1^n y[n] \tag{4.7}$$

ii) subtract the mean of the series from each value

$$z[n] = y[n] - \bar{y} \tag{4.8}$$

iii) Using OLS on the data in (ii), which is taken as having a power law relationship, estimate β, excluding 7/8 of high-frequency power estimates, because this improves the estimates (Eke et al., 2000), and based on the algorithm and codes by Stadnitski (2012).

The procedure was implemented in Studio R, version 3.4.1 (see Appendix A4.1 for the codes used). The algorithm and codes by Stadnitski (2012) were applied to the gross foreign portfolio equity inflow and outflow data for Kenya, Nigeria, South Africa and Zambia,

[50] In Chapter 3 these are classified as *KN_Fepi_Aug2012trBrk and KN_Fepo_Nov2012trBrk* associated with Kenyan data, *NG_Fepo_Apr2015StrBrk* in respect of Nigeria, *SA_Fepi_Jan2006StrBrk* and *SA_Fepo_Jan2006StrBrk* for South Africa, and *ZM_Fepi_Nov2005trBrk* and *ZM_Fepo_Nov2006trBrk* linked to Zambian data.

involving the respective countries' overall samples and the sub-samples. Data for the sub-samples was distinguished by the countries' identified structural breaks, with one set involving data prior to the identified structural break associated with each country's inflows and outflows, and another set consisting of data after the structural break for each class of the foreign portfolio equity flows. For Kenya and Nigeria, however, the estimations were not undertaken for the period prior to the structural break given the short data span of these two countries' data before the respective identified structural breaks. Further, estimations for Nigeria's inflows data were confined to the overall sample only, due to a lack of any structural break identified in the series. All the data used in the estimations were in levels. The results of the PSD estimations are shown in Table 4.1.

4.3.2. The Hurst Exponent (H) Estimation: A Fractal Analysis Approach

In undertaking a fractal analysis to estimate the Hurst coefficient, this study relied on the DFA as the benchmark model. Although the DFA was originally designed for non-stationary data, Løvsletten (2017), nevertheless, found it to be equally consistent for stationary data. In addition, Kirichenko *et al.* (2011) found the DFA to have minimal bias for stationary data, a view supported by Fernandez (2011). These empirical findings, as well as the foreign portfolio equity inflow and outflow data for the four selected sub-Saharan Africa countries broadly being of mixed order of integration in the case of the inflows, and stationary for the outflows, influenced the decision to select the DFA as the benchmark model for undertaking the fractal analysis - in other words, the DFA can handle both stationary and non-stationary series.

For the present study, the Wavelet Method was also applied in estimating the Hurst parameter, specifically as a robustness check of the DFA estimates, since the Wavelet method is an alternative estimation procedure. In addition, wavelet transform methods have become popular in the estimation of the Hurst parameter (Chamoli, et al., 2007; Kantelhardt, 2009; and Kirichenko et al. 2011). The Wavelet Method was also originally designed to deal with non-stationary data (Chamoli, *et al.,* 2007; Kantelhardt, 2009; and Kirichenko et al. 2011, among others). However, Kirichenko *et al.* (2011) and Rea *et al.* (2013) found it equally suitable for stationary data. Additionally, Kirichenko *et al.* (2011) found those estimates which are obtained by the wavelet transformation (just like the DFA method) to have the least bias. In this regard, the estimation method was considered appropriate for use on the data on foreign portfolio equity flows for the four selected SSA countries. It was thus adopted as an alternative estimation method for the sake of ensuring the robustness of the results adopted in this study. Robustness in the context of this research is realised when the estimate from the two methods yields values of the Hurst exponent that falls in the same range as per the usual H exponent classification detailed below or have similar fractal signal classification.

Bhatt, Dedania and Shah (2016); Serinaldi (2010); and Simonsen, Hansen and Nes (1998), among others, provide guidance on the classification or interpretation of the Hurst (H) parameter. The possible values are such that $H \in [0, 1]$ with $0 < H < 0.5$ being an anti-persistent process, meaning there is a tendency for a phenomenon to have its underlying behaviour change more often, which is an aspect of short-range dependence and is like a mean reversion. When $0.5 < H < 1$, a persistent process is implied, meaning that the underlying behaviour of the phenonomenon does not change often. The process is said to be trend reinforcing and is likely to have long-range dependence. When $H = 0.5$, the underlying process is an independent one that is similar to the Brownian motion, akin to be a random walk process because the underlying process of the given phenomenon changes randomly. For $H = 0$, the underlying process of a given data series is said to be uncorrelated, and if $H = 1$, the process is regarded to be self-similar. According to Simonsen *et al.* (1998), to be a self-similar function implies that any transformation done to the given data should yield similar statistical properties as the original series.

With the two methods adopted in this research for estimating the H exponent identified and the H parameter limits defined, the two estimation methods are discussed in the subsections that follow.

4.3.2.1. The Detrended Fluctuation Analysis (DFA) Method

The DFA, credited with Peng et al., (1994), vary as a power law of the form;

$$F(M, n) \propto M^H \tag{4.9}$$

where H is the Hurst exponent and can be estimated by OLS regression of $log(F(M,n))$ on $log(n)$.

The procedure involves the following steps:

(i) From the data (signal), $x[n]$, compute its mean as

$$\bar{x} = n^{-1} \sum_1^n x[n] \tag{4.10}$$

(ii) Subtract the mean from the series $x[n]$ and obtain cumulative mean adjusted sequence to form a new series $y[n]$

$$y[n] = \sum_1^n (x[n] - \bar{x}) \tag{4.11}$$

(iii) Divide $y[n]$ into M non-overlapping windows such that each window has K samples in such a way that $M = \frac{n}{K}$ to obtain a new series denoted $y_m[n]$;

$$y_m[n] = y[mK + n], \qquad 0 \le m \le M - 1, \qquad 0 \le n \le K - 1 \tag{4.12}$$

(iv) In each window, a polynomial of a given degree is fitted to the data in order to obtain a local trend here denoted as $y_{m,t}[n]$.

(v) Subtract the local trend, $y_{m,t}[n]$, from the data, $y_m[n]$, in respective windows to get a detrended sequence (i.e. series of residuals) denoted as $y_{m,d}[n]$.

$$y_{m,d}[n] = y_m[n] - y_{m,t}[n] \tag{4.13}$$

(vi) From the residuals obtained by the previous step, compute the standard deviation for each window and obtain the average of the derived standard deviations denoted as $F(M,n)$.

$$F(M,n) = \sqrt{M^{-1} \sum_1^M \left(y_{m,d}[n]\right)^2} \tag{4.14}$$

For a detailed description of the procedure, see Løvsletten (2017), Lahmiri (2015), Heneghan and McDarby (2000) and Peng et al. (1994).

In this study, the DFA was also implemented in Studio R, version 3.4.1, using a Fractal time series modelling and analysis package called '*fractal*' version 2.0-4. The foreign portfolio equity flows data for Kenya, Nigeria, South Africa, and Zambia were implemented for the respective countries with the same structure and length as described in the previous section on the PSD estimations procedure. The codes used to estimate the data for the four countries are given in Appendix A4.2b, and the results are summarised in Table 4.2.

4.3.2.2. The Wavelet Transform Analysis Method

The Wavelet Transform can be in a continuous or discrete form. In this study the Discrete Wavelets Transform (DWT) was adopted because the data used is of a discrete nature. With the DWT, a given signal is decomposed into filtered series at different time scales. Each filtered series consists of a number of uncorrelated coefficients. The transformation undertaken is such that large time scales provide more low-frequency information about the signal, while small time scales provide more high-frequency information about the signal (Brooks et al., 2008).

In performing the procedure, consider n wavelet transforms. Each transform must have a different scaling coefficient α_i. Also consider $S_1, S_2, S_3, , \ldots, S_n$, as the standard deviations from zero of the respective scaling coefficients α_i to get a ratio of these standard deviations. The ratio of the standard deviations is denoted as $G_1, G_2, G_{3,} \ldots, G_{n-1}$, where, $G_1 = S_1/S_2$, $G_2 = S_2/S_3$, $G_3 = S_3/S_4$, ,..., $G_{n-1} = S_{n-1}/S_n$. Based on these ratios, the average value of G_i is computed as:

$$\bar{G} = \frac{\sum_{i=1}^{n-1} G_i}{n-1} \tag{4.15}$$

The Hurst exponent is $H = f(\bar{G})$, where f is a heuristic function which approximates the Hurst exponent by $\bar{G}$ for stochastic self-affine traces. As per Benoit (1999) software, the algorithm used to perform the estimations in this software sets $n = 4$ and the fractal Dimension (Dw) is computed as $Dw = 2 - H$. For a detailed estimation procedure of steps involved in computing the Hurst parameter using the DWT, see Rehman and Siddiqi (2007).

The same data used in the DFA and the PSD estimation was employed in the DWT procedure, and thus it is of the same properties. The DWT also involved estimations for the overall sample, and for the sub-samples for the periods prior and the periods after the structural break where possible. The results are presented in Table 4.2.

4.3.3. Estimation of the *Correlation Measure*

The DFA estimates of the Hurst parameter obtained in the procedure under 4.3.2.1 were used to manually compute the *correlation measure* using Equation 4.16 below. The *correlation measure* based on the estimated Hurst coefficient helps to establish whether current events (outcome) of a given time series are likely to influence the future outcome or event of the same series. In other words, the *correlation measure* aims at establishing the impact of the present (past) on the future (present) and thereby understand more about the underlying process of the foreign portfolio flows in the SSA countries. In this study, the *correlation measure* was computed using the equation below, in line with Peters (1991):

$$C = (2^{2H-1}) - 1 \tag{4.16}$$

where,

C = *Correlation measure*, and

H = Hurst coefficient

The correlation measure has two possible outcomes that are mutually exclusive:

(a) The time series data under investigation (like the gross foreign portfolio equity inflows and outflows in this case) has a negative correlation, the case of $-1 \leq C < 0$, or

(b) The time series data has a positive correlation, the case of $0 < C \leq 1.0$

If, in the case of this study, the equity portfolio flows have a negative correlation, according to the computed *correlation measure*, it means that current events influencing the behaviour of these gross inflows and outflows have no influence on the future occurrence of these gross flows, which also implies that past events have no consequence on the current behaviour of these gross foreign portfolio equity inflows and outflows. This then infers that the foreign portfolio flows are not trend reinforcing and are more likely to be anti-persistent.

Conversely, if the equity portfolio flows have a positive correlation as an outcome of the *correlation measure* analysis, the implication is that current events driving the gross foreign portfolio inflows and outflows will have an influence on the future occurrence or behaviour of these gross portfolio flows. This could also mean that past events will have a bearing on current outcomes or behaviour of the gross foreign portfolio equity flows. This outcome may likely lead to trend reinforcing in the flows and can be characterised to be a persistent process.

4.3.4. Convergence in the Foreign Portfolio Equity Flows to Steady State Values

The fractal signal classification estimates may yield results suggesting the underlying process of these gross foreign portfolio equity flows to be stationary or anti-persistent (which is a possibility in the outcome space), thus signifying the process to be a mean reversion (as they may be characterised by short-range dependence). Thus, it was considered necessary to estimate the speed of adjustment to the long run steady state value or path to which the gross foreign portfolio equity inflows and outflows revert each time they deviate from their steady state path because of various shocks. This also included estimating the long run average (steady state value) by implication. The procedure was based on the Beta convergence technique (see for example Hlivnjak, 2009; and Monfort, 2008), which is related to the Solow model of the neo-classical growth theory espoused by Solow (1956). The necessity of this undertaking particularly lies in the value of the information on the speed of adjustment of the gross foreign portfolio equity inflows and outflows when reverting to their steady state average. If, for example, the speed of adjustment is sufficiently fast, policy intervention to help the flows revert to their long run average may not be required.

This estimation procedure can also be used to assess whether the data reflects a persistent or an anti-persistent process. Marques (2005) and Dias and Marques (2010) argue that there is a relationship between mean reversion and some degree of persistence via the speed of adjustment to the long run mean in a univariate. In this regard, the data characterised by a relatively slow speed of adjustment to its historical average may have a relatively persistent underlying process. The converse implies: a mean reversion behaviour is akin to an anti-persistent process. This method, therefore, also reinforces the procedures listed above in establishing the underlying behaviour of the foreign portfolio equity flows for the selected countries.

In this study, the estimation of the long run steady state value and the speed of adjustment of the equity portfolio flows were respectively based on Equations 4.17 and 4.18, similar to the ones used by Hlivnjak (2009) and Monfort (2008). The two equations are grounded in the Beta convergence technique of the Solow model of the neo-classical growth theory (Solow, 1956).

$$\Delta x_t = \alpha + \beta_{speed}(x_{t-1}) + \theta_t \tag{4.17}$$

where,

$\Delta =$ The first difference of the variable of interest;

$\alpha =$ The constant term, an autonomous growth in the variable of interest;

$\beta_{speed} =$ The speed of convergence/adjustment to long run mean; and

$\theta_t =$ The error term, such that, $\theta_t \sim N(0, \sigma^2)$.

Equation 5.17, is equivalent to being expressed as

$$x_t - x_{t-1} = \alpha + \beta_{speed}(x_{t-1}) + \theta_t$$

or

$$x_t = \alpha + x_{t-1} + \beta_{speed}(x_{t-1}) + \theta_t$$

or

$$x_t = \alpha + (1 + \beta_{speed})x_{t-1} + \theta_t, \text{ conditioned on } -1 \leq \beta_{speed} \leq 0.$$

The implication of Equation 4.17 is that the speed of adjustment is supposed to be negative if convergence occurs, and therefore an indication of anti-persistence as the underlying process of the time series data. The closer its absolute figure is to one (1) (i.e. 100%), the greater is the speed of adjustment. Specifically, in this study the null hypothesis that was tested was that the variables of interest (i.e. gross foreign portfolio equity inflows and outflows associated with the four sample countries) do not converge to their steady state value; hence $\beta_{speed} \geq 0$. The alternative hypothesis is that the foreign portfolio equity inflows and outflows for the four sub-Saharan Africa countries converge to respective long run steady state path or mean. This is the case if $-1 \leq \beta_{speed} < 0$.

For estimating the long run steady state values for the samples, the equation below was used.

$$Long\ run\ steady\ state = -\frac{\alpha}{\beta_{speed}} \tag{4.18}$$

where,

α and β_{speed} are as defined before.

Although Hlivnjak (2009) and Monfort (2008) used the Beta Convergence estimation procedure in assessing the status of macroeconomic convergence of the Balkan states to the European Union macroeconomic convergence targets, and persistence of inflation in the Euro area, respectively, the intuition behind the technique made it possible to apply it in this study to generate information on the long run average of each country's flows, and particularly the speed of adjustment to the respective long run average for both the gross foreign portfolio inflows and outflows. Thus, whenever such flows are hit by shocks, they may deviate from the long run steady state path, but when the effect of the shock(s) dissipates, they may revert to their steady state value. This is a sign of anti-persistence.

The Beta Convergence estimate in this research was undertaken using the ordinary least square estimation (OLS) procedure. The OLS was preferred because it is ideal for stationary data. The OLS estimations were fitted according to Equation 4.17 with the data for the four countries. This was done for the overall sample as well as the sub-samples for the periods after the identified structural breaks only, because these periods are the most relevant to understanding the behaviour of the flows for the purpose of policy considerations. This is in view of this data set being relatively more recent. Using Equation 4.18 and estimates based on Equation 4.17, the speed of adjustments for the overall sample and the post-structural break sub-samples of respective countries were computed. Both sets of results are shown in Table 4.3.

4.4. Results and Discussion

4.4.1. Fractal Signal Classification

The results of the β estimations for the foreign portfolio inflows (Table 4.1) show that South Africa's entire sample and the series prior to the structural break are anti-persistent but of the fBm signal, and can be considered stationary in nature in that regard. The fractal signal classification results for the full sample, being an anti-persistent fBm as well, is stationary, despite the ACF showing some slowly decaying patterns. The latter, without an understanding of the signal classification, may appear to indicate a relatively persistent process given the slow nature of the decay in its ACFs, as established in the previous chapter. However, after the structural break the series is the fGn type of signal, suggesting the gross foreign portfolio inflows to South Africa may more likely be stationary in nature in the post structural break era as well.

Whilst South Africa's inflows are of mixed signal when structural breaks are considered, Zambia's inflows are of the same signal, the fGn type, for all the three samples considered (i.e. full sample and the two in respect of the periods before and after the identified structural break). The results for the full sample are consistent with the ACFs behaviour shown in the previous chapter, in which the ACFs lie within the bounds. Nigeria's only series, the overall sample (since no structural break was detected in the series) is similarly an fGn signal. Therefore, the inflows to Nigeria and Zambia are more likely to have a stationary process. However, Kenya's inflows, like South Africa's, signal classifications are mixed, being fGn type for the entire sample, but an anti-persistent fBm signal for the sample after the identified structural break of which, overall, has a greater likelihood of being stationary in nature as well.

Table 4.1: PSD's Power Law Estimation Results

Country	*Series*	*Sample Period*	*β Estimate*	*Fractal Signal Classification*
South Africa	Portfolio Inflows	Entire Sample, Jan 1994 - Apr 2018	1.341579	Anti-Persistent fBm
		Before Structural Break, Jan 1994 - Dec 2005	1.766025	Anti-Persistent fBm
		After the Structural Break, Feb 2006 - Apr 2018	0.941077	fGn
	Portfolio Outflows	Entire Sample, Jan 1994 - Apr 2018	1.239102	Anti-Persistent fBm
		Before Structural Break, Jan 1994 - Dec 2005	1.328591	Anti-Persistent fBm
		After the Structural Break, Feb 2006 - Apr 2018	0.4330629	fGn
Zambia	Portfolio Inflows	Entire Sample, Jan 1997 - Sep 2018	0.3593941	fGn
		Before Structural Break, Jan 1997 - Sep 2005	0.7956258	fGn
		After the Structural Break, Nov 2005 - Sep 2018	-0.2721571	fGn
	Portfolio Outflows	Entire Sample, Jan 1997 - Sep 2018	0.276938	fGn
		Before Structural Break, Jan 1997- Sep 2005	0.3943153	fGn
		After the Structural Break, Nov 2005 - Sep 2018	0.5732758	fGn

Kenya	Portfolio Inflows	Entire Sample, Jan 2011 - Sep 2018	0.1058194	fGn
		Before Structural Break, Jan 2011 - Aug 2012	Insufficient Observations	
		After the Structural Break, Sep 2012 - Sep 2018	1.329441	Anti-Persistent fBm
	Portfolio Outflows	Entire Sample, Jan 2011 - Sep 2018	-0.3889706	fGn
		Before Structural Break, Jan 2011- Jan 2013	Insufficient Observations	
		After the Structural Break, Feb 2013 - Sep 2018	-0.4544347	fGn
Nigeria	Portfolio Inflows	Entire Sample, Mar 2013 - Mar 2019	0.0153411	fGn
		Before Structural Break	No structural break detected	
		After the Structural Break	No structural break detected	
	Portfolio Outflows	Entire Sample, Mar 2013 - Mar 2019	0.1580474	fGn
		Before Structural Break, Mar 2013 - Mar 2015	Insufficient Observations	
		After the Structural Break, May 2015 - Mar 2019	2.078443	Random Walk (Brownian motion)

Source: Author, outputs from R Studio using PSD Package.

Regarding the gross foreign portfolio outflows, the signal classification is the same as that of the gross inflows for South Africa and Zambia, even when the structural breaks are considered. To be specific, South Africa outflows are of mixed signal just like the inflow counterparts for the three samples, while for Zambia the outflows are of the same signal as the inflows for all three samples. However for Kenya, the estimates show the outflows to be of the fGn type signal for the entire and post-structural break samples, and hence different from the mixed signal in the case of the inflows. Nigeria's outflows display a fGn type signal for the entire sample, but a random walk process (with an estimated β of about 2.1) for the sub-sample of the period after the structural break. However, if some compact form is considered for Nigeria's data (i.e. bounded), the outflows are then likely to be anti-persistent. The signal classifications in respect of the full samples for Kenya, Nigeria and Zambia are consistent with their respective ACFs, which suggests each series to be stationary.

In all, these results suggest that both gross foreign portfolio equity inflows and outflows for the four sub-Saharan Africa countries considered in this study lack persistence in their behaviour as they are not characterised by a persistent fBm type of signal. Even Nigeria's post-structural break outflows, which appear to lie between a random walk and a weak persistent fBm signal can nonetheless, if given a compact form, be regarded as a stationary process. Thus, the underlying process of the foreign portfolio equity outflows associated with Nigeria is likely to fluctuate within some bounds and, therefore, likely to be a mean reverting process as well.

4.4.2. The Hurst Parameter Estimations and Correlation Measure

Based on the DFA results, and those of the alternative estimation method using the DWT, the foreign equity portfolio inflows to all the four countries may be characterised as being stationary, and thus anti-persistent for both the full samples and the sub-samples prior to and after the identified structural breaks, where applicable. This is largely consistent with the PSD (signal classification) estimates above. The Hurst parameter estimates fall in the range $0 < H < 0.5$ (Table 5.2). These results suggest that the respective countries' gross foreign portfolio equity inflows have short-range dependence as past events are more likely not to have a bearing on current and future occurrence and behaviour. This is confirmed by the respective computed *correlation measures*, which are negative in each case. The negative signs of the *correlation measure* implies that current (or past) events or behaviour related to the gross foreign portfolio equity inflows in one cycle (or period) have no influence on the occurrence or behaviour of future (or current) gross foreign portfolio equity inflows in subsequent cycle (period) (Table 4.2). This, therefore, inhibits any possibility of trend reinforcing behaviour in this class of the gross foreign portfolio equity flows in the four SSA countries.

Similar DFA results were obtained with regard to the gross foreign portfolio equity outflows, indicating that they are also anti-persistent with $H \in (0, 0.5)$. However, exceptions were found to the DWT estimates for the Nigerian and Zambian post-structural break periods, where Hurst parameter values were found to be above 0.5. However, since the process for Zambia's outflows is of the fGn signal classification, the anti-persistence condition holds. The underlying process of the Nigerian gross foreign portfolio equity outflows may also be stationary if the random walk process is characterised by some compact form (bounded) as argued before. There is, therefore, robustness in the results that suggests the gross foreign portfolio equity outflows to be stationary based on the alternative estimations. Similarly, results for the individual country *correlation measure* infers that these gross portfolio equity outflows too are of short-range dependence, and are thus anti-persistent (*i.e.*, like the inflows, they are not trend reinforcing).

Table 4.2: The Results from the DFA and Wavelet Estimations

Description				*Hurst Coefficient*	*Fractal Dimension*	*Correlation Measure*	*Signal Classification*
South Africa	Portfolio Inflows	Entire Sample, Jan *1994 - Apr 2018*	DFA	0.19052370	1.8094763	-0.348856512	Anti-Persistent fBm
			Wavelet	0.376	1.624	-0.157937	
		Before Structural Break, Jan *1994 - Dec 2005*	DFA	0.2436930	1.7563070	-0.299048758	Anti-Persistent fBm
			Wavelet	0.441	1.559	-0.0785358	
		After Structural Break, Feb *2006 - Apr 2018*	DFA	0.09022279	1.90977721	-0.433383083	fGn
			Wavelet	0.249	1.751	-0.2938728	
	Portfolio Outflows	Entire Sample, Jan *1994 - Apr 2018*	DFA	0.1740848	1.8259152	-0.363527715	Anti-Persistent fBm
			Wavelet	0.279	1.721	-0.2638866	
		Before Structural Break, Jan *1994 - Dec 2005*	DFA	0.205233	1.794767	-0.335442471	Anti-Persistent fBm
			Wavelet	0.289	1.711	-0.2536108	
		After Structural Break, Feb *2006 - Apr 2018*	DFA	0.08013597	1.91986403	-0.44125112	fGn
			Wavelet	0.037	1.963	-0.4736844	
Zambia	Portfolio Inflows	Entire Sample, Jan *1997 - Sep 2018*	DFA	0.05406995	1.94593005	-0.46108117	fGn
			Wavelet	0.043	1.957	-0.4692884	
		Before Structural Break, Jan *1997 - Oct 2005*	DFA	0.08233582	1.91766418	-0.439544536	fGn
			Wavelet	0.208	1.792	-0.3328884	
		After Structural Break, Dec *2005 - Sep 2018*	DFA	0.04051821	1.95948179	-0.471111167	fGn
			Wavelet	0.053	1.947	-0.4618799	
	Portfolio Outflows	Entire Sample, Jan *1997 - Sep 2018*	DFA	0.05808474	1.94191526	-0.458073358	fGn
			Wavelet	0.024	1.9759	-0.483012967	
		Before Structural Break, Jan *1997 - Oct 2006*	DFA	0.09229913	1.90770087	-0.431749773	fGn
			Wavelet	0.784	1.216	0.48246701	
		After Structural Break, Dec *2006 - Sep 2018*	DFA	0.06734284	1.93265716	-0.451073201	fGn
			Wavelet	0.641	1.359	0.215879283	

Kenya	Portfolio Inflows	Entire Sample, Jan *2011 - Sep 2018*	DFA	0.1074288	1.8925712	-0.419705323	fGn
			Wavelet	0.081	1.919	-0.4405814	
		Before Structural Break, Jan *2011 - Jul 2012*	DFA Wavelet	Insufficient Observations			
		After Structural Break, Sep *2012 - Sep 2018*	DFA	0.1031315	1.8968685	-0.423152049	Anti-Persistent fBm
			Wavelet	0.317	1.799	-0.3393308	
	Portfolio Outflows	Entire Sample, Mar *2013 - Mar 2019*	DFA	0.1371191	1.8628809	-0.395322333	fGn
			Wavelet	0.149	1.851	-0.3852806	
		Before Structural Break, Jan *2011 - Jan 2013*	DFA Wavelet	Insufficient Observations			
		After Structural Break, Feb *2013 - Sep 2018*	DFA	0.08682716	1.91317284	-0.436044075	fGn
			Wavelet	0.045	1.955	-0.4678149	
Nigeria	Portfolio Inflows	Entire Sample, Mar *2013 - Mar 2019*	DFA	0.05806095	1.94193905	-0.45809123	fGn
			Wavelet	0.101	1.899	-0.424854053	
		Before Structural Break	DFA Wavelet	No structural break detected			
		After Structural Break	DFA Wavelet	No structural break detected			
	Portfolio Outflows	Entire Sample, Mar *2013 - Mar 2019*	DFA	0.1509144	1.8490856	-0.383646982	fGn
			Wavelet	0.055	1.945	-0.460385882	
		Before Structural Break, Mar *2013 - Mar 2015*	DFA Wavelet	Insufficient Observations			
		After Structural Break, May *2015 - Mar 2019*	DFA	0.1653924	1.8346076	-0.371151323	Border line of Persistent and anti-persistent fBm
			Wavelet	0.742	1.258	0.398616083	

Source: Author, outputs from R Studio using fractal Package and Benoit Software.

The results depicted in this study are consistent with the findings of Sarno and Taylor (1999) and Cai, Dang and Lai (2016) in their respective studies of the underlying behaviour of the foreign portfolio equity inflows to developing countries. In both cases, the estimations, based on state space methods, established that equity portfolio flows to developing countries are anti-persistent as they were found to be transitory in nature. The findings in this research is also in line with what Bluedorn et al. (2013) and Levchenko and Mauro (2007) established about foreign portfolio equity flows, as pointed out in the literature review. Thus, the results of this study are in line with what has thus far been found with regards to foreign portfolio equity flows elsewhere in the world, albeit using different estimation techniques.

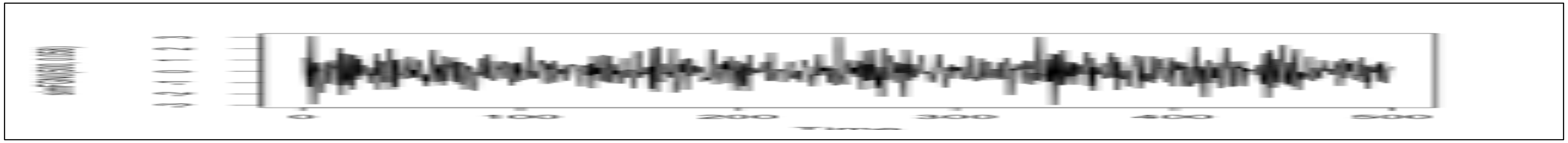
4.4.3. Simulated Sample Paths for the SSA's FPEFs based on the *H* and β Results

When the signal classification (β) and the Hurst parameter (H) results are combined to generate sample paths for respective countries' foreign portfolio equity inflows through simulations, the results confirm that the underlying process for each country's inflows are indeed of the stationary type as indicated by the visualisation of each sample path generated as shown in Figure 4.2. The simulations are done using *somebm* (for the series that has the fBm signal classification) as well as *longmemo* (for the series with fGn signal) packages of Studio R involving 500 observations (see Appendix A4.2 for the Studio R codes used to undertake the simulations).

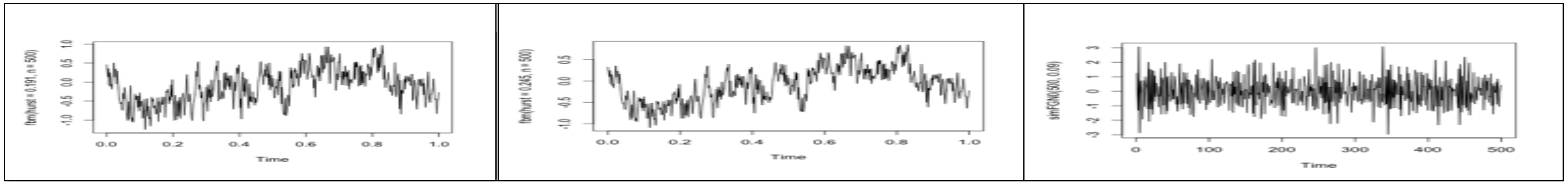
Similarly, the sample paths obtained through simulations based on the outflow's signal classification and the estimated H parameter results confirms that these flows have a stationary underlying process and are thus anti-persistent as well as shown in Figure 4.3 (see Appendix A4.2 for the Studio R codes). The simulation confirms that the foreign portfolio outflows associated with Nigeria in the post structural break era can be regarded as a stationary process if it is bounded, as it fluctuates within a relatively narrow bound. Therefore, with some compact form, Nigeria's foreign portfolio equity outflows are likely to be anti-persistent and therefore stationary.

Kenya

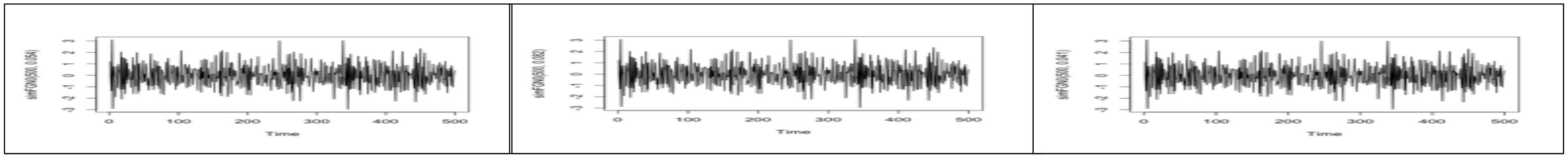
Nigeria



South Africa



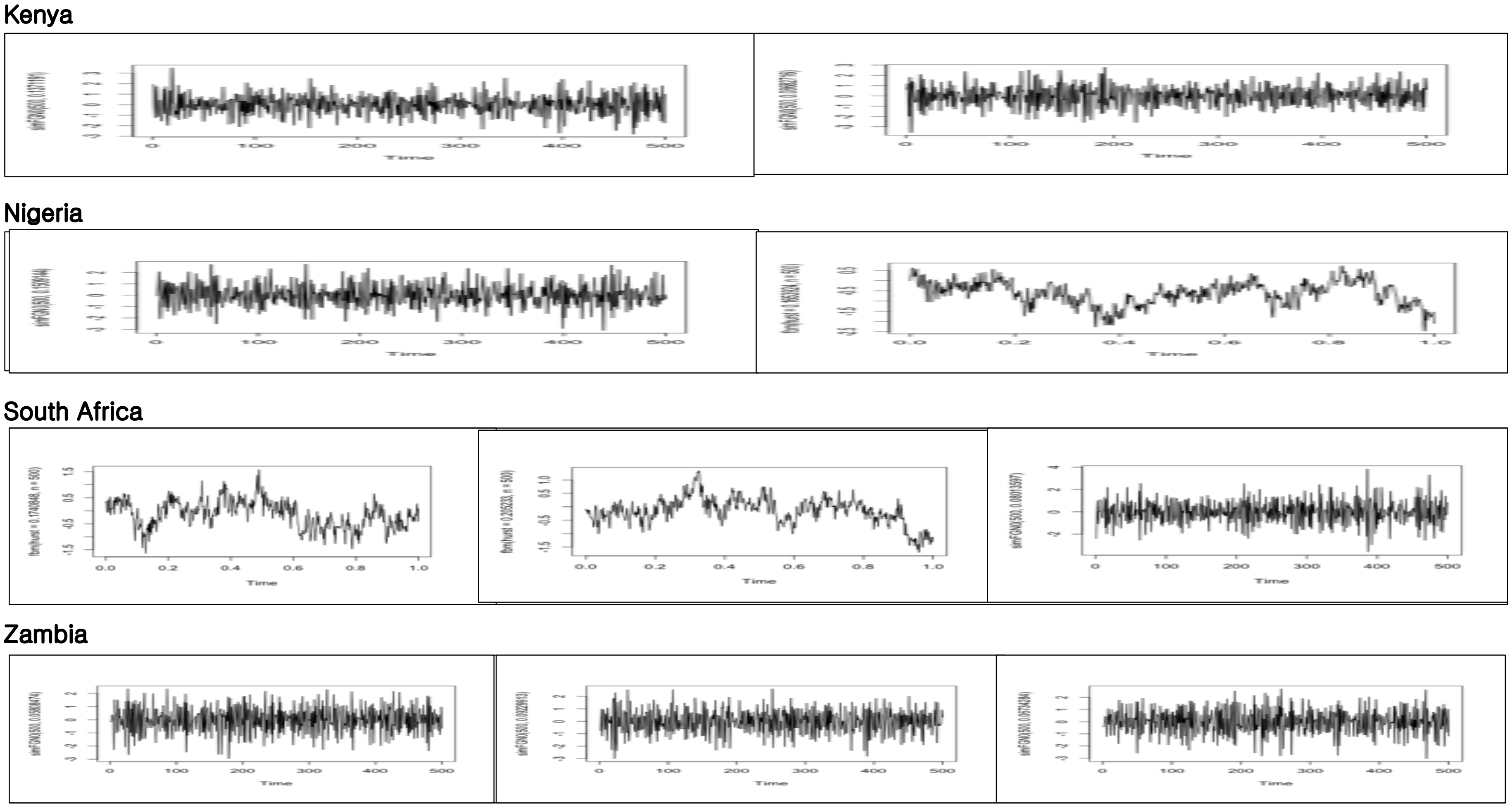
Zambia



Source: Studio R Simulations using *longmemo* and somebm packages.

Note: Charts on the left are for the overall sample and those on the right are for the period after the structural break. Middle charts are for the period before the structural break.

Figure 4.2: Simulated Underlying Process of the Inflows using fBm or fGn Signal and *H* Values.



Source: Studio R Simulations using *longmemo* and *somebm* packages
Note: Charts on the left are for the overall sample and those on the right are for the period after the structural break. Middle charts are for the period before the structural break.

Figure 4.3: Simulated Underlying Process of the Outflows using fBm or fGn Signal and *H* Values

4.4.4. FPEFs Convergence to their Steady State Values and Speed of Adjustment

The results for the estimated β (i.e. β_{speed}) was found to have a negative sign in each case (Table 4.3), and thus the null hypothesis that there is no convergence for the four sub-Saharan Africa countries' gross foreign portfolio equity inflows and outflows to their respective long run averages was rejected. This implies that when a shock to the four sampled countries' gross foreign portfolio equity inflows and outflows deviates these flows from their respective long run steady state averages or the steady state path, these gross foreign portfolio equity inflows and outflows are more likely to get back to their respective steady state levels or path. Therefore, these flows do not diverge from their steady state path, but rather display mean reverting behaviour, which is common among stationary or anti-persistent processes. Further, the negative sign of the β_{speed} coefficient is indicative of the underlying processes of the foreign portfolio equity flows associated with Kenya, Nigeria, South Africa and Zambia being anti-persistent. This is consistent with the findings in the previous sections.

In each case, especially after the structural breaks, the estimated respective speeds of adjustments (value of β_{speed} coefficient) for both the gross foreign portfolio equity inflows and outflows are very high. This means that these gross foreign portfolio equity inflows and outflows are highly likely to revert to their respective steady state levels or path within a relatively short period of time. Zambia has the highest speed of adjustment followed by Nigeria (see Table 4.3). South Africa has the lowest speed of adjustment among the four countries. The high speed of adjustment for the gross foreign portfolio equity outflows associated with Nigeria and the negative sign of its coefficient is indicative of the outflows being anti-persistent, despite the PSD results suggesting that they could be a random walk process.

Comparing the results of the β_{speed} coefficients of the inflows and outflows to their steady state values indicates the speed of adjustment for the outflows to be higher than for the inflows in Kenya, South Africa, and Zambia. This means that a surge in the outflows is relatively shorter lived than a surge in the inflows, thus supporting the possibility of the stock exchanges experiencing greater net inflows than net outflows.

Table 4.3: Summary Results of the Beta Convergence

Country	Type of Flows	Sample		Variable coefficients	Std. Error	t-Statistics	Probability Values.	Long Run Steady State Value (Millions of USD)	Speed of Convergence to the steady state value (%)
South Africa	Inflows	Full	α	301.319	100.215	3.007	0.00290	4,188.9479	-7.1932
			Β	-0.0719	0.0218	-3.2985	0.00110		
		After Struct Break	α	2510.9580	415.7798	6.0392	0.00000	6,021.7419	-41.6982
			Β	-0.4170	0.0676	-6.1724	0.00000		
	Outflows	Full	α	335.9461	105.1428	3.1951	0.00160	3,928.8265	-8.5500
			Β	-0.0855	0.0236	-3.6206	0.00030		
		After Struct Break	α	3321.3460	448.1498	7.4112	0.00000	5,918.8414	-56.1100
			Β	-0.5611	0.0742	-7.5628	0.00000		
Zambia	Inflows	Full	α	1,534,177	315,662.30	4.8602	0.00000	1.6266	-94.3200
			Β	-0.9432	0.0621	-15.1773	0.00000		
		After Struct Break	α	2,183,214	512,893.40	4.2567	0.00000	2.2161	-98.5200
			Β	-0.9852	0.0811	-12.1511	0.00000		
	Outflows	Full	α	1,498,854	392,600.30	3.8178	0.00020	1.5301	97.9600
			Β	-0.9796	0.0622	-15.7394	0.00000		
		After Struct Break	α	2,440,838	710,470.00	3.4355	0.00080	2.4063	-101.4350
			Β	-1.0144	0.0845	-12.0046	0.00000		
Kenya	Inflows	Full	α	30,395,935	7,239,178.00	4.1988	0.00010	80.7606	-37.6370
			Β	-0.3764	0.0824	-4.5685	0.00000		
		After Struct Break	α	58,003,559	10,456,354.00	5.5472	0.00000	92.1793	-63.0000
			Β	-0.6292	0.1084	-5.8041	0.00000		
	Outflows	Full	α	31,279,774	7,139,150.00	4.3814	0.00000	77.2903	-40.4705
			Β	-0.4047	0.0841	-4.8148	0.00000		
		After Struct Break	α	65,167,519	11,050,408.00	5.8973	0.00000	91.5455	-71.1859
			Β	-0.7119	0.1149	-6.1940	0.00000		
Nigeria	Inflows	Full	α	111.86090	27.3158	4.0951	0.00001	206.9203	-54.0599
			Β	-0.5406	0.1067	-5.0677	0.00000		
	Outflows	Full	α	68.29378	23.50917	2.9050	0.00490	214.9130	-31.7770
			Β	-0.31777	0.088112	-3.6065	0.00060		
		After Struct Break	α	111.63910	23.70321	4.7099	0.00000	139.8880	-79.8060
			Β	-0.79806	0.143566	-5.5588	0.00000		

The long run steady state values computed for each country show that South Africa's foreign portfolio equity inflows for the overall sample period was estimated to be around US $4.19 billion, which is US$ 28.0 million higher than the historical average of US $3.91 billion for the full sample period (Table 3.2a in the immediate past chapter). However, the estimated long run steady state averages for the other countries were in the neighbourhood of their respective historical averages for their respective full samples. For example, Kenya's estimate for the entire sample was US $80.760 million, compared to the US $80.536 million historical average for the full sample, while the estimate for Nigeria was US $206.920 million, compared with the US $210.141 million historical average recorded for the covered sample period. In the case of Zambia, the estimated and the actual historical average values were similarly virtually identical at US $1.626 million and US $1.617, respectively.

Similar results were obtained in respect of the gross foreign portfolio equity outflows (Table 4.3 and Table 3.2a in the previous chapter). These results indicate that the long run steady state average of the foreign portfolio equity outflows from South Africa for the entire sample period to be US $3.93 billion against the US $3.713 billion historical average for the same period. With respect to Zambia, the estimates of US $1.530 million were virtually the same as the historical average of US $1.527 million. Similarly, Kenya's estimated long run steady state value was broadly in line with the historical average at US $77.290 million and $75.978 million, respectively. Nigeria's long run steady state value was estimated to be US $214.913, broadly in line with the US $219.333 million historical average computed for the series in Chapter 3.

As the estimated values for the full sample periods are generally close to the respective historical averages, this gives an idea of the level to which foreign portfolio equity flows, for the given sample, may gravitate to once deviated from their steady state path by various shocks. In all cases, the estimated long-run steady state values of the inflows are higher than those of the outflows. In view of this, on average, each country could be regarded as having recorded more inflows than outflows over the respective sample periods. This seem to be consistent with the argument in respect of the inference based on the speeds of adjustment stated earlier. In this context, some of the sub-Saharan Africa stock markets looked at in this study may have derived a net benefit from the foreign portfolio equity flows. Like argued before, having higher levels of inflows relative to the outflows enhances stock market liquidity.

Although the estimated steady state values after respective structural breaks are also in the neighbourhood of their respective historical averages, they are nevertheless higher for Kenya, South Africa, and Zambia[51] for both the inflows and outflows than for the respective overall sample values. This is also true for the speeds of adjustment in each case. Nonetheless, Zambia's net flow position based on long-run average estimates was negative in the period after the identified structural break, while it was positive for Kenya and South Africa. Therefore, Kenya and South Africa's stock exchanges are more likely to have benefited from the foreign portfolio equity flows given an average positive net flow over their respective post-structural break periods compared to Zambia. A global surge in the inflows to emerging markets following the implementation of the UMP by the US FRB in late 2008 may explain the increase in the net inflows recorded for Kenya and South Africa in the period after their respective structural breaks. Zambia, on the other hand, may not have benefited from the surge in the inflows as there was a corresponding rise in the recorded outflows. This was likely due to the deterioration in its economic fundamentals in the period after 2013 owing to a huge fiscal deficit the Zambian government was running, with an attendant risk of rising foreign debt. A risk aversion strategy towards Zambia's assets among the foreign portfolio investors emerged as a result, leading to a net outflow of foreign portfolio equity funds.

As indicated before, Nigeria is a unique case in this study due to the lack of a structural break in its inflows over the considered study period. Therefore, it is not possible to assess its net portfolio flows in the period after a structural break as the case has been with the other three countries. However, the estimated long run steady state value of its foreign portfolio outflows in the period after the structural break is lower than for the entire sample, unlike the other three countries, which is another factor that also makes it a unique case. The lower value of its long run average after the structural break compared to the one for the overall sample is an indication that there were lower outflows in the later years than before the structural break. This could be attributed to the foreign

[51] Nigeria is not included because no structural break was detected in the inflows

exchange restrictions that was imposed by the Central Bank of Nigeria to stem the fall in its foreign reserves (IMF, 2016a) after the end of the UMP in 2015 that led to capital flight from emerging and frontier market economies and, subsequently, depreciation of their currencies (IMF, 2016c). In essence, foreign portfolio equity investors who needed to exit the market may have found challenges to get foreign exchange due to such restrictions. The other three countries never imposed foreign exchange restrictions during the period.

4.5. Implications of the Results

The PSD estimations for signal classification results provide therefore, some evidence that the foreign portfolio equity flows in the selected sub-Saharan Africa countries may have an underlying process that is stationary and possibly mean reverting. The implication of this on stock market development for the selected countries is that those countries with a steady state value where inflows are higher than the outflows could benefit from higher liquidity related with more inflows. Further, for these countries, an increase in stock market capitalisation may arise from the stock price increases owing to the higher demand accompanying higher inflows. This argument arises from the fact that since these flows tend towards mean reversion, any undesirable deviation from their steady state path will most likely be short lived. In terms of policy, given that these flows are inherently stable, and any uncharacteristic behaviour is likely to be temporal, the PSD estimation results suggest that pursuing or maintaining a liberalised capital account policy is advisable.

The Hurst parameter estimates and the way in which the gross foreign portfolio equity inflows and outflows respond to shocks in terms of their speeds of adjustment, based on the beta convergence estimation procedure, have implications on stock market development and on the nature of the policy approach to their management. From the policy perspective, these results, just like the PSD's, also suggest that these flows may not require capital controls but probably capital account liberalisation as the gross foreign portfolio equity flows associated with the four sub-Saharan Africa countries are anti-persistent in nature, with a possibility of mean reversion. The rationale with this policy suggestion going by the Hurst parameter estimates is that any undesirable behaviour from these flows (*e.g.* a sharp rise in the foreign portfolio equity outflows that may lead to stock price decline or a surge in the inflows resulting in price bubbles) will likely be short-term in nature. Thus, given the anti-persistent behaviour and relatively high speed of adjustment, sooner than later, these flows will undergo a correction, and largely revert to their long-run steady state value or path after being hit by a shock. Therefore, this anti-persistent and mean reversion underlying property in the data implies that it may be sub-optimal to use capital controls to try to address the undesirable behaviour of these foreign portfolio equity flows in the four sub-Saharan Africa countries. Financial liberalisation in this regard may be more optimal a policy for foreign portfolio equity flows in the four sub-Saharan Africa countries.

This estimation outcome also underscores the need to avoid responding, in the context of policy, to the noise. Given that in time series data the observable component is the noise component, there is therefore a possibility that policy makers may respond to the noise in the data each time the undesirable behaviour is noted or observed in the foreign portfolio equity flows. This is especially so in the absence of knowledge about the underlying process, which is the signal and the unobservable component of a given time series data. As observed by Blanchard, L'Huillier and Lorenzoni (2013), noise play a critical part in short run dynamics and, depending on the severity of the noise, may compel policy makers to intervene. Since the gross foreign portfolio equity inflows and outflows are characterised by high volatility and accordingly associated with much noise, this may invoke emotion-based reactions among those observing the behaviour of these flows when under intense volatility, likely with no regard for its underlying process. This, therefore, may lead to policy makers reacting to the noise and not the signal.

Since any policy undertakings can be expensive, the signal classification and the Hurst parameter properties of a given class of gross foreign capital inflows and outflows should therefore be considered before contemplating policy options to avoid policy regrets. For example, if the Brazilian policy authorities had taken into account the finding by Sarno and Taylor (1999) that gross foreign portfolio equity and bond inflows to Brazil were anti-persistent, they may not have imposed capital controls in 2009, which may have turned out to be sub-optimal. As shown by Chamon and Garcia (2016), this action was followed by a slow-down in the Brazilian economy, likely in part as a result of the imposition of these controls, as the nation may have been starved of foreign savings to augment the domestic savings and thus leverage its economy. In fact, Brazil's economy at the time was characterised by low levels of domestic savings that needed to be augmented by foreign capital inflows (Chamon and Garcia, 2016). It is well-known that foreign investors do not respond well to capital controls (Hughes, 2006). If Brazil had not at the time responded to the noise (volatility) in these flows, the cooling off may well have led to a rebound in inflows in the absence of capital controls, especially considering that from 2010 there was a broad global recovery in capital flows to emerging markets, albeit with heightened volatility, following the implementation of the UMP through bond purchase programme by the US Federal Reserve Bank (Fofack, Aker and Rjoub, 2020; Sahay *et al.*, 2014; and Balakrishnan *et al.*, 2013).

In view of these results, it is also imperative for sub-Saharan Africa policy makers to be cognisant of the underlying process of foreign portfolio equity flows to and from their countries in policy decision making to avoid policy regrets. This is particularly critical as these countries all need foreign savings, including in the form of portfolio equity inflows to help augment domestic resources as well as to boost the liquidity of their respective stock markets.

The estimations performed and the period-specific results discussed above, confirms that it is necessary to account for structural breaks when undertaking empirical works involving financial or economic time series data, which is especially critical for monofractal analysis, as in the case of this study. This allows for an investigation of whether there is a possibility of multifractal behaviour in time series data under consideration, given the different fractal signal classes occurring on either side of the identified structural break for some countries. Further, given the link between signal classification and the Hurst exponent, knowledge of signal classification in view of the structural break may be helpful in modelling financial time series data, owing to the differences in behaviour of the data on either side of the structural break for some countries. This may also be important in extracting policy (or strategy related) relevant information. For example, given the results for South Africa, a policy maker who bases decisions solely on the estimations using the overall sample may design a policy intervention that could be sub-optimal. Although the two series are both found to be of short-range dependence, for the period after the structural break the estimations show that the portfolio flows have a tendency of stabilising relatively faster after a shock than is the case with the full period covered by the study.

In addition, these results have implications on forecasting or predicting the direction of the foreign portfolio equity flows. An understanding of the underlying process of these flows can help in anticipating the likely behaviour of the flows in the next episode given the knowledge about their initial condition. In the four SSA countries, given the anti-persistent behaviour, one can easily tell that a rise in the flows in one period (if that is the initial condition at a particular time) will be accompanied by a decline in the foreign portfolio equity flows in the next period. This knowledge may be incorporated in forecasting the direction of portfolio equity flows not just for the four SSA countries, but also other countries whose foreign portfolio equity flows data may be subjected to fractal analysis that includes fractal signal classification. Therefore, knowledge of the underlying process can play an important role in predicting or forecasting the future direction of not just the foreign portfolio equity flows, but also other classes of foreign capital flows since such flows are time series type of signals. This may help with capital flows management from the available policy options.

Further, the results from this study that suggest these flows to be largely anti-persistent for all four countries under study, and is consistent with the empirical findings on foreign portfolio equity flows for some Latin American and Asian countries as established in literature (for example by Cai et al., 2016; Becker & Noone, 2009; and Sarno and Taylor, 1999a and 1999b), implies that fractal analysis when applied to many countries data on foreign capital flows can play an important role in developing theories on the underlying behaviour of not just the foreign portfolio equity flows, but also other classes of foreign capital flows. This is because with an understanding of the underlying behaviour of each class of foreign capital flows for many countries there is a possibility of establishing the general underlying behaviour of each class of capital flows, and thereby contribute towards formulating a theory or theories on the underlying behaviour of foreign portfolio equity flows and other classes of foreign capital flows. Such theories could play a role on capital flows management from the policy perspective.

Overall, the results on the four countries assessed in this study show that their respective flows, although all anti-persistent in behaviour, respond differently in terms of the time taken to recover from shocks. While shocks may die out relatively slowly for South Africa's two classes of foreign portfolio equity flows judging by the speed of adjustment to the steady state value (and also decays in the ACFs patterns established in Chapter 3), they fizzle out relatively quickly for Zambia. Nigeria and Kenya lie somewhere in between. One explanation for this may be differences in the depth of the four markets as well as their degree of capital account openness. The JSE is a far bigger market in terms of both market capitalisation and number of listings than the LuSE, while the NgSE and NSE lies in between, although both are far bigger than the LuSE. However, Zambia and Kenya have completely open capital accounts, with no restrictions on capital inflows and outflows (Ellyne and Chater, 2016). South Africa, on the other hand, still has some exchange controls in place on its capital account, particularly for capital outflows, although capital inflow constraining measures have been fully lifted (Ellyne and Chater, 2016). Thus, in general repatriation of funds out of South Africa requires permission from the South African Reserve Bank (SARB). Although Nigeria allows for the free movement of capital in and out of the country, the process is embryonic, and requires much documentation, especially after 2015. Of the four countries covered by this study, Nigeria can be ranked second to South Africa in terms of capital flow restrictions (Ellyne and Chater, 2016).

In view of the results being anti-persistent, since these findings show that adverse shocks on the flows will not persist, suggest that quantitative controls or limitations are not warranted, and hence that financial liberalisation could be an optimal policy option (as opposed to assuming capital controls) in these four SSA countries.

4.6. Chapter Summary

In this chapter, an understanding of the underlying process of foreign portfolio equity flows for Kenya, Nigeria, South Africa, and Zambia was sought, specifically with regards to whether the process is random, anti-persistent, or persistent. The methodology used to establish the true underlying process included fractal signal classification of the data based on power spectral density estimation of the power law. This approach is necessary to determine whether the data is fBm or fGn type of signals. This is helpful in avoiding making an ambiguous interpretation of the estimated Hurst parameter. In this study the Hurst coefficient was estimated using the DFA, while the Wavelet approach was used to test the results for robustness and whose results were interpreted in light of the fractal signal classification estimated results. Based on the estimated Hurst parameter, the *correlation measure* was computed to determine whether past (present) events related to these portfolio flows have no bearing on current (future) events of these equity flows in each country.

The results suggest that gross foreign portfolio equity inflows and outflows in the four SSA countries are not a random walk, and neither are they persistent. Specifically, they are anti-persistent, they are stationary, and are thus of short-range dependence (with a possibility of being a mean reversion process) and potentially predictable. As a stationary type of process, the convergence to their steady state and the respective speeds of adjustment to the steady state of each class of the gross foreign portfolio equity flows was computed based on the Beta convergence technique. The results confirm their stationarity or anti-persistent behaviour with negative signing of the respective coefficients for the speed of adjustment.

The implication of these results is that shocks to both the inflows and the outflows do not have a long-lasting impact in each country, because their deviation from the steady state path following any given shock is relatively short lived. From the policy point of view, these findings suggest that pursuing or maintaining financial liberalisation in the four countries could be a more optimal policy option than assuming capital controls, as the latter does not appear warranted when mean reversion occurs relatively quickly following shocks.

In the next chapter, the impact of the gross foreign portfolio equity inflows and outflows on market capitalisations (and thus stock market development) for the four SSA countries is separately undertaken within the Bayesian estimation framework, based on sign restrictions, of the *Calderon-Rossell* dynamic partial equilibrium model. The chapter also describes the research methodology for undertaking dynamic impact assessment of gross foreign portfolio flows on stock market capitalisation.

Chapter 5

Impact of Foreign Portfolio Equity Flows on Stock Market Capitalisation: A Bayesian Analysis

5.1. Introduction

In this chapter, an empirical analysis to establish the impact of the gross foreign portfolio equity inflows and outflows on the market capitalisations of the stock exchanges for Kenya, Nigeria, South Africa, and Zambia is discussed. The analysis is based on the *Calderon-Rossell* theoretical proposition by Calderon-Rossell (1991 and 1990), which is a comprehensive theoretical exposition on stock market development. It is estimated with Bayesian techniques and addresses objective number 3 of this study. The justification for adopting the Bayesian technique is that Bayesian methods, as established in literature, are good for data with a short span, which is the case with the data sets of most SSA countries, particularly with regards to foreign portfolio equity flows. It is also suitable for data with different orders of integration, unlike other methods that may only be useful for data with the same order of integration.

In implementing the Bayesian method for the estimation of the extended *Calderon-Rossell* partial equilibrium model with impulse responses to show the dynamic impact of shocks on market capitalisation, this research therefore extends the works of el-Wassal (2005), Yartey (2008), Yartey (2010), and Sezgin et al. (2015), among others. Specifically, it uses a different estimation method from those employed previously, which did not estimate impulse response functions. Further, this builds on the work of Ng, Ibrahim and Mirakhor (2016) whose Bayesian techniques to study the effect of capital flows on stock market development utilised the *Calderon-Rossell* model, but similarly did not generate the impulse response functions to show the dynamic impact of the shock to the flows on stock market capitalisation. Lastly, it builds on the work of Eniekezimene (2013), which estimated stock market development using market capitalisation as a proxy and included foreign portfolio equity flows in the estimation employing an error correction method, although without utilising the *Calderon-Rossell* model.

5.2. FPEFs Impact on Stock Market Capitalisation: A Mathematical Derivation

In this section, a mathematical model postulating the relationship between foreign portfolio equity flows and stock market capitalisation is formulated in terms of how the inflows and outflows are separately likely to impact stock market capitalisation. As has been empirically established in literature by Li et al. (2017), Wang et al. (2016) and others as documented by Ho (2019), foreign portfolio equity flows tend to affect stock markets' capitalisation.

The mathematical derivations used are micro founded, in which case the relationship between foreign portfolio flows and market capitalisation is considered first at firm level, and then extended to the entire market as described below.

1) Foreign portfolio equity flows at a firm level among the companies listed at an exchange takes the following form:

   i $$fpei_{t,i} = \gamma^{fpei}{}_{t,i}(OS_{t,i}) \times SP_{t,i}\,, \quad i = 1, 2, \ldots, k-1, k \tag{5.1a}$$

   ii $$fpeo_{t,i} = \gamma^{fpeo}{}_{t,i}(OS_{t,i}) \times SP_{t,i} \quad i = 1, 2, \ldots. k-1, k \tag{5.1b}$$

   where,

   $fpei_{t,i}$ = Foreign portfolio equity inflows.

   $\gamma^{fpei}{}_{t,i}$ = Proportion of shares in firm i purchased by foreign investors at time t.

   $OS_{t,i}$ = Outstanding shares of firm i at time t.

   $SP_{t,i}$ = Price of shares of firm i at time t.

   $fpeo_{t,i}$ = Foreign portfolio equity outflows.

   $\gamma^{fpeo}{}_{t,i}$ = Proportion of shares in firm i sold by foreign investors.

2) It should be noted that the product of the price of the shares and the number of outstanding shares gives market capitalisation ($MktCap$) formally defined in Equation 5.2 below.

   $$MktCap_t = OS_t \times SP_t \tag{5.2}$$

3) From the equations above, it implies that the values of foreign portfolio equity inflows and foreign portfolio equity outflows associated with a particular firm are proportions of the firm's market capitalisation.

   Let,

   $vfpih_{t,i}$ = Value of foreign portfolio investors holdings in firm i; and

$\gamma^{vfpih}{}_{t,i}$ = Proportion of shares in firm i held by foreign investors.

Therefore,

$$vfpih_{t,i} = \gamma^{vfpih}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}] \tag{5.3a}$$

Similarly, the value of domestic investors' holdings in the firm is a proportion of the firm's MktCap.

Let,

$vdih_{t,i}$ = Value of domestic investors holdings in a firm, say i; and

$\gamma^{vdih}{}_{t,i}$ = Proportion of shares in firm i held by domestic investors.

Therefore,

$$vdih_{t,i} = \gamma^{vdih}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}] \tag{5.3b}$$

In view of the formal definitions of the values for both domestic and foreign investors' holdings of shares in the firm (Equations 5.3a and 5.3b) and considering Equation 5.2, market capitalisation of the firm, therefore, takes the following form:

$$MktCap_{t,i}^{firm} = \gamma^{vfpih}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}] + \gamma^{vdih}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}] \tag{5.4}$$

4) The interaction of foreign and domestic investors is such that foreign investors can buy shares from domestic investors (the case of foreign portfolio equity inflows). The same can also be done with foreign investors exiting the market (the case of foreign portfolio equity outflows). Equally, domestic investors can purchase shares from foreign investors who are exiting the market (also the case of foreign portfolio equity outflows). This interaction leads to a change in the proportion of the stock of shares held by foreign investors as there could be a gain or loss. Subsequently, the value of foreign portfolio investors' holdings in the firm will change accordingly. Specifically, this will be influenced by the previous period's stock holding of the firm's total

outstanding stock[52] plus the net change due to inflows (purchases) and outflows (sales).

Therefore,

$$vfpih_{t,i} = \gamma^{vfpih}{}_{t-1,i}[(OS_{t,i}) \times SP_{t,i}] + \gamma^{fpei}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}] - \gamma^{fpeo}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}] \quad (5.5a)$$

And satisfies the following condition:

$$\gamma^{vfpih}{}_{t-1,i}(OS_{t,i}) \geq \gamma^{fpeo}{}_{t,i}(OS_{t,i}).$$

It therefore follows that market capitalisation for a firm ($MktCap_t^{firm}$) at a particular time will be a sum total of the values of equity holdings among the foreign and domestic investors in the firm and takes the form presented below.

$$MktCap_{t,i}^{firm} = \gamma^{vfpih}{}_{t-1,i}[(OS_{t,i}) \times SP_{t,i}] + \gamma^{fpei}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}] + \gamma^{vdih}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}] - \gamma^{fpeo}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}]$$

Let,

$$\alpha_{t,i} = \gamma^{vfpih}{}_{t-1,i}[(OS_{t,i}) \times SP_{t,i}]$$

That is,

$$MktCap_{t,i}^{firm} = \alpha_{t,i} + \gamma^{fpei}{}_{t,i}(OS_{t,i}) \times SP_{t,i} - \gamma^{fpeo}{}_{t,i}(OS_{t,i}) \times SP_{t,i} + \gamma^{vdih}{}_{t,i}(OS_{t,i}) \times SP_{t,i}$$

Therefore,

$$MktCap_{t,i}^{firm} = \alpha_{t,i} + (\gamma^{fpei}{}_{t,i} - \gamma^{fpeo}{}_{t,i})(OS_{t,i} \times SP_{t,i}) + \gamma^{vdih}{}_{t,i}[(OS_{t,i}) \times SP_{t,i}] \quad (5.5b)$$

5) To help establish the nature of relationship between foreign portfolio equity flows and market capitalisation, one may consider the net foreign portfolio equity flows. This is formally defined in Equation 5.6 below.

$$\eta_t = fpei_t - fpeo_t \quad (5.6a)$$

Thus, net foreign portfolio equity flows associated with firm i at time t takes the form presented in Equation 5.6b below.

[52] This assumes no corporate finance decisions that can change the stock of outstanding shares in the two periods.

$$\eta_{t,i} = fpei_{t,i} - fpeo_{t,i} \qquad (5.6b)$$

Investors' trading behaviour, including foreign portfolio equity investors whose motivation is not to buy and hold (that is, their main interest is not dividend earnings but rather capital gains by buying low and selling high[53]), may lead to a net foreign portfolio equity inflows or outflows associated with firm *i* shares at time *t* represented formally by the relationship below.

$$\eta_{t,i} = \gamma^{fpei}{}_{t,i}(OS_{t,i}) \times SP_{t,i} - \gamma^{fpeo}{}_{t,i}(OS_{t,i}) \times SP_{t,i}$$

$$\eta_{t,i} = [\gamma^{fpei}{}_{t,i}(OS_{t,i}) - \gamma^{fpeo}{}_{t,i}(OS_{t,i})] \times SP_{t,i}$$

$$\eta_{t,i} = (\gamma^{fpei}{}_{t,i} - \gamma^{fpeo}{}_{t,i}) \times (OS_{t,i} \times SP_{t,i}) \qquad (5.6c)$$

Arising from Equations 5.5b and 5.6c, therefore,

$$MktCap_{t,i}^{firm} = \alpha_{t,i} + \eta_{t,i} + \gamma^{vdih}{}_{t,i}(OS_{t,i}) \times SP_{t,i} > 0 \qquad (5.7)$$

6) For the entire exchange, market capitalisation is the sum of individual listed firm's market capitalisation at any given time. To determine market capitalisation value for the entire stock exchange at time t, Equation 5.7 is summed up to obtain:

$$\sum_{i=1}^{k} MktCap_{t,i}^{firm} = \sum_{i=1}^{k}[\alpha_{t,i} + \eta_{t,i} + \gamma^{vdih}{}_{t,i}(OS_{t,i}) \times SP_{t,i}]$$

Let,

$$\beta_t = \sum_{i=1}^{k}[\gamma^{vdih}{}_{t,i}(OS_{t,i}) \times SP_{t,i}],$$

$$MktCap_t^{Excg} = \alpha_t + \beta_t + \eta_{t,} > 0 \qquad (5.8)$$

where,

$MktCap_t^{Excg}$ = Market capitalisation for an entire stock exchange;

η_t = Net foreign portfolio equity flows for the entire exchange;

α_t = Value of previous period's foreign investors' stock market's holding.

β_t = Value of domestic investors' equity holding at the exchange;

[53] There may of course also be other reasons for selling low, such as a need for liquidity.

It should however, be noted that stock market capitalisation value can also change due to corporate finance decisions made by individual firms[54] as this will have a bearing on the listed shares outstanding. The decisions include those related to delisting, new listing, share buyback, mergers and acquisitions (M&A), share splitting or consolidation, and rights issue, among others.

Since there is now interest in literature to also analyse the gross foreign portfolio outflows as opposed to only focusing on the net foreign portfolio equity flows and gross foreign portfolio equity inflows[55], the likely individual impact of the gross foreign portfolio equity inflows and outflows on stock market capitalisation from the theoretical perspective, is now considered.

7) Based on Equations 5.6's definition of net foreign portfolio equity flows and Equation 5.8, it follows that;

$$MktCap_t^{Excg} = \alpha_t + \beta_t + (FPEI_{t,} - FPEO_{t,}) \tag{5.9}$$

where,

$FPEI$= Foreign portfolio equity inflows for the entire market.

$FPEO$= Foreign portfolio equity outflows for the entire market.

Differentiating Equation 5.9 in terms of market capitalisation of the exchange with respect to each of the two classes of the foreign portfolio equity flows, yields the following results:

i The case of stock market capitalisation and foreign portfolio equity inflows.

$$\frac{\partial\,(MktCap_t^{Excg})}{\partial(FPEI_t)} = 1 > 0 \tag{5.10}$$

This indicates that changes in foreign portfolio equity inflows are likely to have a positive effect on market capitalisation.

[54] Stock market capitalisation in other words may not necessarily be influenced by market decisions alone that are reflected in stock price changes.

[55] See, for example, Guichard (2017); Eichengreen, Gupta, and Masetti (2017); and Eichengreen et al. (2017).

ii The case of stock market capitalisation and foreign portfolio equity outflows.

$$\frac{\partial\ (MktCap_t^{Excg})}{\partial(FPEO_t)} = -\ 1 < 0, \tag{5.11}$$

This shows that changes in foreign portfolio equity outflows may largely have a negative impact on stock market capitalisation. However, there is also a possibility that if a proportion of stocks being sold by one group of foreign investors lead to low supply in the secondary market when demand for the same by domestic and another group of foreign investors is relatively higher, then the impact of foreign portfolio equity outflows on stock market capitalisation can be positive and therefore lead to a rise in stock market capitalisation.

The outcomes in Equations 5.10 and 5.11 have implications on modelling the impact of gross foreign portfolio equity inflows and outflows on stock markets capitalisation. Arising from these results, it is expected that foreign portfolio equity inflows should have a positive signing in a linear equation while foreign portfolio equity outflows will have a negative signing. Similarly, in a Bayesian VAR with sign restrictions, as shown in literature by Uhlig (2005) for example, the sign restriction on the market capitalisation variable in response to a positive shock to foreign portfolio equity inflows will have to be a positive sign. In the same vein, a sign restriction on market capitalisation in response to a positive shock to foreign portfolio equity outflows could be a negative sign. Nonetheless, a positive restriction is a possibility as well for the argument given above.

The formal relationship between stock market capitalisation and foreign portfolio equity flows derived above may render support towards establishing a formal theory on the behavioural interaction of foreign portfolio equity flows and stock market capitalisation and thus stock market development. At present this seem to be lacking in literature from the search so far done by this author.

5.3. The Calderon-Rossell Model

In the behavioural structural model of stock market development credited to Calderon-Rossell (1991 and 1990), stock market capitalisation is used as a proxy, and is determined by economic growth and stock market liquidity. The model is formulated as follows (see for example Sezgin and Atakan, 2015; Yartey, 2008; and el-Wassal, 2005):

$$M = PV \tag{5.12a}$$

where,

M = Stock Market Capitalisation value in local currency.

V = Number of listed companies shares at a given stock market.

P = Average prices in local currency of listed companies.

In the *Calderon-Rossell* model, M is determined by economic growth (G) and stock market liquidity (T). Economic growth plays two fundamental roles. Firstly, it increases investors' incomes, who in turn increase the demand for shares. This drives prices up, causing market capitalisation to increase on account of price. Secondly, economic growth expands companies' opportunities, leading to an increase in revenues and profits that consequently raises stock prices, owing to the increase in demand among those investors chasing dividends and/or capital gains. This may further create an incentive for corporates to issue more shares, and consequently could also increase market capitalisation on account of increased outstanding shares.

On the role of liquidity, two possible effects are identified in the model when liquidity increases. The first one is the likely increase in appetite for the corporates' shares, in which case more shares could be issued that increase market capitalisation if there is no dilution in share prices. The second one relates to the possibility of share price decline on average after issuance of new shares. This may emanate from the increase in supply of the shares and may cause market capitalisation to decline (el-Wassal, 2005).

In this regard, it follows that:

$$M \equiv PV = M(G, T) \tag{5.12b}$$

$$P = P(G, V)$$

$$V = V(P, T)$$

Expressing these relationships in reduced form as growth rates (Sezgin & Atakan, 2015), one obtains;

$$\log(M) = \beta_1 \log(G) + \beta_2 \log(T) \tag{5.12c}$$

$$\log(P) = \varphi_1 \log(G) + \varphi_2 \log(T) \tag{5.12d}$$

$$\log(V) = \omega_1 \log(G) + \omega_2 \log(T) \tag{5.12e}$$

Combining equations $(5.12d)$ and $(5.12e)$ one gets;

$$\log(P) + \log(V) = \varphi_1 \log(G) + \varphi_2 \log(T) + \omega_1 \log(G) + \omega_2 \log(T)$$

$$\log(P) + \log(V) = (\varphi_1 + \omega_1) \log(G) + (\varphi_2 + \omega_2) \log(T)$$

But,

$$\log(M) \equiv \log(PV) = \log(P) + \log(V)$$

Therefore,

$$\log(M) = (\varphi_1 + \omega_1) \log(G) + (\varphi_2 + \omega_2) \log(T) \tag{5.12f}$$

where,

$$\beta_1 = (\varphi_1 + \omega_1)$$

$$\beta_2 = (\varphi_2 + \omega_2)$$

Modifications or extensions to the reduced form behavioural equation $(5.12f)$ have been devised to include other financial and macroeconomic variables, in addition to institutional quality variables, as done by el-Wassal (2005), Yartey (2008), Yartey (2010), and Sezgin and Atakan (2015), for example.

As established in literature, Garcia and Liu (1999) identified two ways to study stock market capitalisation, namely an institutional and a macroeconomic approach. This guides the choice of variables in the estimations additional to the variables in the original *Calderon-Rossell* dynamic partial equilibrium model.

5.4. The Bayesian Framework for Empirical Analysis

The Bayesian approach works in three steps as follows:

a) Setting a prior belief about a parameter of interest (θ) that needs estimation. This reflects the knowledge, or conversely, the state of ignorance, a researcher has concerning the parameter of interest before the data (y) is observed. The prior is characterised as a distribution such as $P(\theta) \sim N(\widetilde{\theta_0}, \Sigma_0)$ if it is a normal distribution, for example.

b) Collecting the data (y) and setting the likelihood, $\mathcal{L}(y/\theta)$, which is the data generating process; and

c) Computing the posterior, expressed as Equation 5.13 below, by combining the prior information in (a) and the likelihood in (b). This is synonymous with updating the prior information with the information contained in the data and is based on the Bayes Theorem (Equation 5.11a).

$$P(\theta/Y) = \frac{P(y/\theta)P(\theta)}{P(y)} \tag{5.13a}$$

for which $P(y)$ is a data density that can be evaluated through integration as

$$P(y) = \int (y/\theta)P(\theta)d\theta \tag{5.13b}$$

Thus, the posterior takes the form;

$$P(\theta/Y) = \frac{P(y/\theta)P(\theta)}{\int (y/\theta)P(\theta)d\theta} \tag{5.13c}$$

The posterior is of fundamental interest in Bayesian estimations as it provides more information about the parameters of interest , θ, given the available data, y (Koop et al, 2007). The function $P(y/\theta)$ is the likelihood, (and may also be expressed as $\mathcal{L}(y/\theta)$), and implies that a value of θ for which $P(y/\theta)$ is large is more likely to be "true" than the value of θ for which $P(y/\theta)$ is small. Inferences, as well as decisions about θ following an observation of the data y, is based on the information contained in the likelihood function for the observed y.

Generally, the Bayesian approach to estimation requires the use of Bayes' rule for eliciting a probability statement about what is unknown (such as the parameter of a given model or whether a model is a correct one or otherwise) conditional on what is known, the data in this case (Koop et al, 2007).

In general, inferences or decisions about θ, which is an unknown parameter, can be achieved through either the frequentist (also referred to as the classical) approach or the Bayesian approach. In the frequentist approach, θ is fixed (while in a Bayesian approach it is considered a random variable) and its probability is represented by a long-run frequency of a repetitive experiment. Probability quantifies variability and the uncertainty that arises from randomness. The measure of uncertainty in the frequentist approach is through the p-value or level of significance advanced by Fisher (1925) and Neyman and Pearson (1933), respectively. For instance, a level of significance of five percent ($\alpha = 5\%$) implies a ninety-five percent confidence interval ($CI = 95\%$) in repeated sampling. Nonetheless, this does not imply in probability that the true value of θ has a 95% chance (probability) of being true (an de Schoot and Depaoli, 2014). However, Bayesian probability quantifies uncertainty such that a 95% credibility interval is a statement that there is a 0.95 probability of finding θ in the 95% interval (an de Schoot and Depaoli, 2014).

Bayesian methods are increasingly being employed in finance and economics related empirical works and are usually based on the vector autoregression (VAR) modelling approach to address various research questions[56]. In a typical VAR equation of ρ dimensional row random vector y_t, such as Equation 5.14 below, one can incorporate the prior beliefs by setting the moments of the prior distribution of the coefficients in Equation 5.15.

$$y_t = \alpha + \sum_{i=1}^{L} \boldsymbol{B}_i y_{t-L} + \varepsilon_t \tag{5.14a}$$

where,

$t = 1, -----, T$;

$\alpha = 1 \times \rho$ unknown vector of intercepts;

$\boldsymbol{B}_i =$ unknown $\rho \times \rho$ matrix of coefficients, $i = 1, -----, L$; and

$\varepsilon_t = \varepsilon_1, -----, \varepsilon_T$, the independent and identically distributed error terms.

The error terms are normal, i.e. $N_\rho(0, \theta)$ with $\rho \times \rho$ unknown covariance matrix $\boldsymbol{\theta}$.

Equation 5.14a can be expressed in a Bayesian set up as summarised in Equation 5.14b derived as follows:

[56] See, for example, Yin & Ma (2020), Balta & Vašíček (2020), and Tevdovski, Petrevski, and Bogoev (2019) on the recent application of the technique.

$$\mathrm{P}(\mathrm{B},\theta/y_{1-L:t}) = \frac{\mathrm{P}(\mathrm{B},\theta)P(y_{1-L:t}/\mathrm{B},\theta)}{P(y_{1-L:t})}$$

Since the interest of a researcher is in the parameters (B, θ), the expression '$P(y_{1-L:t})'$ in the equation above can be ignored because it does not contain any parameter, and thus this equation can be summarised as in Equation 6.3b below.

$$\mathrm{P}(\mathrm{B},\theta/y_{1-L:t}) \propto \mathrm{P}(\mathrm{B},\theta)P(y_{1-L:t}/\mathrm{B},\theta) \qquad (5.14\mathrm{b})$$

where,

i. $\mathrm{P}(\mathrm{B},\theta/y_{1-L:t})$ is the joint posterior distribution of the VAR(L)'s coefficients and contains the information present in the prior distribution conditioned on the information about the sample data. Therefore, the posterior distribution captures the information at hand used in making inferences about the parameters of the VAR.

ii. $\mathrm{P}(\mathrm{B},\theta)$ is the prior distribution and its role is to capture the information related to model parameters 'prior' to observing the data. It therefore summarises initial information as per researchers' own understanding about the model parameters.

iii. $P(y_{1-L:t}/\mathrm{B},\theta)$ is the likelihood function, as it contains all the information about the sample parameters.

The VAR in Equation 5.14a may have the unknown matrix of its regression coefficients $\alpha'$and β_i' represented by $\boldsymbol{\Phi}$ as in Equation 5.15 for the respective first and second moments[57].

$$E\left[(\boldsymbol{\Phi}_k)_{i,j}\right] = \begin{cases}\delta \ if \ j = i, k = 1 \\ 0 \quad \text{otherwise}\end{cases}, \qquad V\left[(\boldsymbol{\Phi}_k)_{i,j}\right] = \begin{cases}\dfrac{\lambda_1\lambda_2}{k}\dfrac{\sigma_i}{\sigma_2}, \ k = 1, \dots\dots, p \\ \lambda_0\sigma_i,\end{cases} \qquad (5.15)$$

where, $(\boldsymbol{\Phi}_k)_{i,j}$ represents the elements in position (i,j) in matrix $\boldsymbol{\Phi}$, and $\boldsymbol{\delta}$ is the prior mean that takes the values 0 or 1. If the VAR is specified in levels, $\delta = 1$, but if the VAR's specification is in growth rates, then $\delta = 0$. The hyper parameter λ_1 controls the overall

[57] See for example Bańbura, Giannone, and Reichlin, (2010), and Yin and Ma (2020).

tightness with regard to the way the prior influences the posterior distribution. If $\lambda_1 \rightarrow 0$, or indeed $\lambda_1 = 0$, the posterior equals the prior and the data do not influence the estimates. When $\lambda_1 \rightarrow \infty$, the posterior expectations are consistent with the ordinary least square (OLS) estimates.

Additional priors, *sum of coefficients priors* and *dummy initial observations priors,* incorporating beliefs of unit roots and cointegration respectively, have been introduced into the Bayesian VAR methodology following the works of Doan et al. (1984) and Sims (1993) to improve forecasting ability of the Bayesian VARs. With regard to the use of the hyperparameters by researchers in Bayesian VARs, a number of them largely follow approaches for the baseline specifications[58].

5.5. Methodology

Consider a reduced form VAR Equation 5.14, presented in Section 5.4 with n endogenous variables. This is taken as the equation to summarise the sampling information contained in the data for the four sampled SSA countries used to determine the impact of foreign portfolio equity inflows and outflows on stock market capitalisation, based on the *Calderon-Rossell* model. From the equation, ε_t might not have economic interpretation since its elements may be cross correlated among the equations in the VAR system (Enders, 2008). However, economic meaning may be extracted from the structure because in economic theory, a one step ahead forecast errors of a reduced form VAR is linked to structural innovations (see for instance Chadha et al., 2010; Cha and Bae, 2011; and Danne, 2015) in such a way that;

$$\boldsymbol{A}\varepsilon_t = e_t \tag{5.16}$$

where, $\boldsymbol{A}$ is an $n \times n$ matrix of structural parameters with e_t being the structural shocks such that $e_t \sim iid(0,1)$. The structural parameters can be recovered from the reduced form VAR by invoking on the system the property;

$$\boldsymbol{A}\acute{\boldsymbol{A}} = \Sigma = E[\varepsilon_t \acute{\varepsilon}_t] \tag{5.17}$$

[58] These baseline specifications are outlined in Bańbura, Giannone, and Reichlin, (2010); Giannone et al. (2015); Carriero et al. (2015); and Giannone et al. (2014).

The $E[\varepsilon_t \acute{\varepsilon_t}]$ can then be obtained by estimating the VAR using the Ordinary Least Square (OLS) method. To specifically recover the structural shocks from the estimated $\widehat{\varepsilon_t}$, there is need for the identification of $\boldsymbol{A}$**.** For the detailed procedure involved, see, for example, Enders (2008), Chadha et al. (2010), Cha and Bae (2011), and Danne (2015).

The identification procedure used in this study is an alternative to the traditional Cholesky decomposition method, and follows the Uhlig (2005) method, a Bayesian approach with sign restriction. Traditional methods to identification are inconsistent with the sign restriction approach, but the latter's use to generate impulse responses consistent with economic theory is only possible with the use of Bayesian techniques (Granziera, Moon and Schorfheide, 2018; and Danne, 2015). This therefore is another justification for the adoption of sign restriction-based Bayesian techniques.

With the Bayesian techniques involving sign restrictions, cumulative impulse responses are computed to check whether the range of the impulse responses is compatible with the sign restrictions imposed. A Bayesian VAR with sign restrictions is thus estimated in each successful draw with an uninformative prior, usually the uniform distribution, used as a prior distribution in the second round of the Bayesian procedure undertaken to make the draws. The Bayesian process is achieved through a Markov Chain Monte Carlo (MCMC) process. Since there is a possibility of generating rejected draws, the credibility of the process (how well the model is specified) is judged by the number of rejected draws (Danne, 2015). Zero or few rejections implies the estimation process is good. However, too many rejections are indicative of the presence of better alternative models that fit the data and satisfies sign restrictions (Fry and Pagan, 2011 and Danne, 2015).

In this study, the Uhlig (2005) penalty function method, a Bayesian estimation technique with sign restrictions, whose technical detail can be found in Uhlig (2005); Chadha et al. (2010); Busch et al. (2010); and Danne (2015), was used. This technique was implemented using *VARsignR*[59] package from the Comprehensive R Archive Network,

[59] The accompanying manual can be accessed at: https://cran.r-project.org/web/packages/VARsignR/VARsignR.pdf

based on Danne (2015)'s work. The robustness test of the estimations was done using the Fry and Pagan (2011) Median – Target (MT) method.

The use of other variables in the extended *Calderon-Rossell* model follows the lead of Garcia and Liu (1999) based on their macroeconomic approach, in line with the available data for the four SSA countries. Monthly data was applied to the modified *Calderon-Rossell* model in order to study the impact of gross foreign portfolio equity inflows and outflows on stock market capitalisation. Estimations were done country by country, so as to establish how each country is affected, drawing from the findings of Boero, Mandalinci and Taylor (2019) and Magud, Reinhart, and Rogoff (2018), who have argued that country circumstances may matter in the success of capital flow management.

5.5.1. Sign Restrictions: Impact of FPEIs on SSA Stock Markets' Capitalisation

In addition to the variables of interest being foreign portfolio equity inflows (*fpei*) and market capitalisation (*mcap*), both measured in US dollars for the respective countries, as well as a measure of stock market liquidity which in this study is market turnover (*mto*), the following macroeconomic variables were used:

i Real private sector credit (*rpsc*), as a proxy variable for economic activity for Kenya, Nigeria and Zambia, whilst for South Africa this was proxied by PVMP as per the detailed description of each variable presented in Chapter 3.

ii Headline inflation (*inf*), playing the role of domestic sector macroeconomic stability, taken as the annual change in respective countries' consumer price index as per detailed description in Chapter 3.

iii Nominal exchange rate (*exr*), used to capture external sector dynamics, consistent with Olugbenga (2012). The nominal exchange rate was adopted because movements in exchange rates have a valuation effect on market capitalisation as well if measured in dollar terms. There is thus a possibility of stock market capitalisation mimicking dynamics in the exchange rate, with an appreciation coinciding with a rise in market capitalisation, or a reduction in the case of a depreciation.

Two sign restrictions were imposed on foreign portfolio equity inflows and market capitalisation in each case. The other variables, namely the economic activity indicator, exchange rate, headline inflation, and market turnover, were not restricted, except for Zambia's exchange rate variable, to which a negative restriction was applied that resulted into a better-behaved model than otherwise. The order of arrangement of the variables does not matter (Danne, 2015). The restrictions applied are summarised in Table 5.1.

Table 5.1: Sign Restrictions for the Portfolio Inflows Shock Identification

Kenya	Shock/Variable	*fpei_kn*	*nse_mcap*	*rpsc_kn*	*exr_kn*	*inf_kn*	*nse_mto*
	fpei_kn	+	+	?	?	?	?
Nigeria	Shock/Variable	*fpei_ng*	*ngse_mcap*	*rpsc_ng*	*exr_ng*	*inf_ng*	*ngse_mto*
	fpei_ng	+	+	?	?	?	?
South Africa	Shock/Variable	*fpei_sa*	*jse_mcap*	*Pvmp*	*exr_sa*	*inf_sa*	*jse_mto*
	fpei_sa	+	+	?	?	?	?
Zambia	Shock/Variable	*fpei_zm*	*luse_mcap*	*rpsc_zm*	*exr_zm*	*inf_zm*	*luse_mto*
	fpei_zm	+	+	?	-	?	?

Note: the sign "?" implies no restriction imposed

The sign "+" implies a positive shock, leading to an increase in the variable of interest. Therefore, the identification above implies that a positive shock to the gross foreign portfolio equity inflows will cause market capitalisation to increase. This is consistent with the mathematical proposition on the relationship between foreign portfolio equity inflows and stock market capitalisation in Section 5.2. The rationale is that foreign portfolio equity inflows may likely create a secondary market demand shock, leading to share prices increasing. This identification is also consistent with the empirical evidence of el-Wassal (2005), Yartey (2008), Yartey (2010), Eniekezimene (2013) and Sezgin et al. (2015), who all found a positive relationship between market capitalisation and some measure of foreign capital inflows. A negative ("-") sign imposed on Zambia's exchange rate variable implies that a positive shock to the foreign portfolio equity inflows leads to the appreciation of the exchange rate of the Zambian Kwacha to the US dollar.

In implementing these restrictions, unrestricted VARs were used for each country's data. All the variables, except for inflation, entered in log-level and the lags for each unrestricted VAR were based on the Akaike information criterion (AIC), the Schwarz information criterion (SC), and the Hannan-Quinn information criterion (HQ). The resulting stable VARs (since none of the characteristic roots were outside the unit circle) were eventually the ones estimated by Bayesian techniques with sign restrictions. Based on these lag length criteria, the lag lengths adopted for the respective countries' VARs were two lags for South Africa and Zambia and one lag for Kenya and Nigeria (see also Studio R Codes in Appendix A5.1). To generate the impulse vector and the candidate impulse to which the penalty-method algorithm was applied, 800 draws from the posterior and 800 sub-draws for each posterior draw were made for all the countries except South Africa, which required only 500 draws in both cases to reach convergence (see R Codes in Appendix A5.1). This is probably the result of the relatively longer data set for South Africa compared to the other three countries, as described in Chapter 4. Thus, the data for South Africa covered the period January 1994 - April 2018 (292 observations), Zambia's covered the period January 1997 to September 2018 (261 observations), Kenya's was based on the period January 2011 to September 2018 (93 observations) and Nigeria's involved the period March 2013 to March 2019 (73 observations). The impact of the shock for each country was restricted to a period of up to six months from the first period of the shock's impact.

Following the foreign portfolio equity inflow structural breaks identified for each country (except Nigeria) in Chapter 3, a similar procedure as for the overall sample was undertaken. However, estimations were restricted to starting periods of February 2006 for South Africa, September 2012 for Kenya, and December 2005 for Zambia, as was done with the empirical work in Chapter 4. The sign restrictions' specifications were the same as in the overall sample. However, the lag length for South Africa was different, where one lag length was used as recommended by the SC and HQ criteria. The VARs used also had their characteristic roots lying within the unit circle and were therefore stable VARs.

5.5.2. Sign Restrictions: Impact of FPEOs on SSA Stock Markets Capitalisation

Apart from the foreign portfolio equity outflows (FEPOs) variable, the other variables used in estimating the impact of the outflows on market capitalisation were the same as those used in exploring the impact of the FPEI on the SSA stock markets' capitalisation. To get well behaved VARs, four and three sign restrictions were imposed in respect of the South African and Zambian variables, respectively (Table 5.2), but only two restrictions were imposed on the Kenyan and Nigerian variables.

Table 5.2: Sign Restrictions for the Portfolio Outflows Shock Identification

Kenya	Shock/Variable	*fpeo_kn*	*nse_mcap*	*rpsc_kn*	*exr_kn*	*inf_kn*	*nse_mto*
	fpeo_kn	+	?	?	+	?	?
Nigeria	Shock/Variable	*fpeo_ng*	*ngse_mcap*	*rpsc_ng*	*exr_ng*	*inf_ng*	*ngse_mto*
	fpeo_ng	+	?	?	+	?	?
South Africa	Shock/Variable	*fpeo_sa*	*jse_mcap*	*Pvmp*	*exr_sa*	*inf_sa*	*jse_mto*
	fpeo_sa	+	?	?	+	+	+
Zambia	Shock/Variable	*fpeo_zm*	*luse_mcap*	*rpsc_zm*	*exr_zm*	*inf_zm*	*luse_mto*
	fpeo_zm	+	?	?	+	+	?

Unlike the inflows' identification strategy, no restriction was imposed on market capitalisation because its response to *fpeo* may not be asymmetrical for two reasons, briefly highlighted in Section 5.2. Firstly, the *fpeo* transactions create a supply shock in the secondary market. If demand is relatively low compared to supply for the issues held by foreign portfolio investors, this might lead to the equities being sold at a price relatively lower than what may have prevailed in the previous trading period. This is because investors may likely want to protect the targeted capital gains realised. This may contribute negatively to market capitalisation and could lead to its decline, *ceteris paribus*. Secondly, the outcome will be even worse if there is a *flight to safety* transaction strategy among foreign investors in order to minimise losses as much as possible. However, if demand in the market for the issues held by foreign investors who are exiting the market is higher than can be offloaded (supply), this may neutralise/minimise the secondary market supply shock. A share price increase is more likely in this case, and may affect market capitalisation positively, leading to its increase, *ceteris paribus*. These likely transaction events can make the response of market capitalisation symmetric to the *fpeo* shock. Therefore, this warrants a no identification (sign) restriction to the likely response of market capitalisation to the *fpeo* shocks.

The sign restrictions imposed on the other variables imply that a positive shock to the portfolio outflows should lead to the exchange rate depreciating owing to the rise in demand for foreign currency. This is due to foreign investors repatriating their funds. Headline inflation rises on impact as a result of the pass-through from the exchange rate depreciation of the domestic currency. The sale of shares by foreign portfolio investors may also lead to an increase in the value of transactions (market turnover) on impact.

The data in all cases covered the same periods as for the inflows, and hence the number of observations were again 292, 261, 93 and 73 for South Africa, Zambia, Kenya and Nigeria, respectively. Just as for portfolio inflows, the procedure for South Africa again used two lags (see Appendix A5.1) following the AIC, SC, and HQ criteria suggestions. However, the estimation procedures for the other three countries were based on one lag, as suggested by the SC. The specification strategies adopted for each country yielded well-behaved VAR models, as all their characteristic roots were contained within the unit circles.

Given the structural breaks on the foreign portfolio equity outflows identified in Chapter 3, an estimation to establish the behaviour of market capitalisation emanating from shocks to foreign portfolio equity outflows after the structural break was also undertaken. Thus, the impact of FPEOs on Kenya's Nairobi Securities Exchange's market capitalisation was estimated for the period February 2013 to the end of the sample period. All the specifications and restrictions were the same as in the overall sample, except that in this estimation two lags were used to get a stable VAR. For South Africa, the estimation was from February 2006 to the end of the sample period, and the sign restrictions were only two, both positive, in respect of the foreign portfolio equity outflows and exchange rate variables. One lag length was used as per SC and HQ suggestions and this estimation strategy yielded a stable VAR.

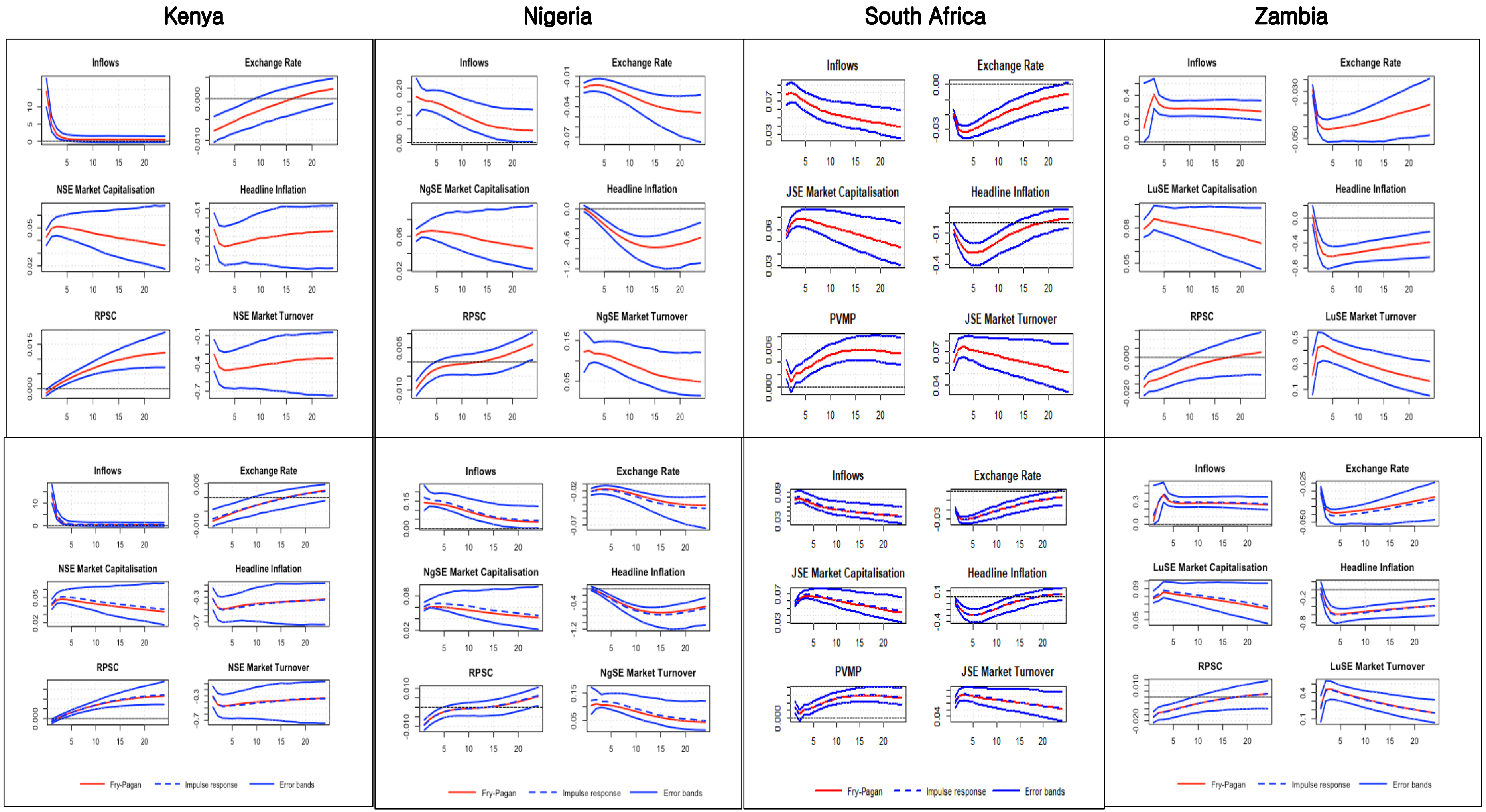
The estimation of the impact of outflows on the market capitalisation of Zambia's LuSE considered data from November 2005 to the end of the sample period. All the specifications and restrictions were the same as in the overall sample, except that one lag was used to yield a stable VAR, as per the AIC and HQ suggestions. The impact of FPEOs on the NgSE market capitalisation was estimated with data from May 2015 to the end of the sample period. A VAR with one lag was used and four sign restrictions (all positive) were imposed on the foreign portfolio equity outflows variable, the exchange rate, the proxy for real economic activity (*rpsc_ng*), and inflation. A positive restriction was imposed on *rpsc_ng* because a depreciation makes exports competitive, and in turn may likely cause a rise in real economic activity, but at the expense of a rise in inflation. For the other variables, restrictions were imposed for the same reasons as advanced in respect of similar variables for the other three countries. These restrictions were necessary to obtain robust estimates in respect of the impact of foreign portfolio equity outflows associated with Nigeria on the market capitalisation of the NgSE after the structural break.

5.6. Results and Discussion

The results are presented in Figures 5.1a to 5.2b below and summarised in Tables A5.1 – A5.4 in the appendix. The results indicate that a shock to the foreign portfolio equity inflows (top left for each country) leads to inflows rising rapidly on impact, and then subsequently declining to reach the steady state in the fourth month for Kenya but lasts relatively longer for Nigeria. The increase for South Africa and Zambia lasts up to the third month before declining. In each case, the foreign portfolio equity inflows show some evidence of anti-persistence given that the inflows fall after the initial rise. However, the decline for Zambia lasts two months. They nonetheless appear to be stable, which is an indication of anti-persistence.

Similarly, the estimations of the data in the post structural break era also show a contemporaneous rise in the gross foreign portfolio equity inflows following a positive shock. However, the rise is short-lived for Zambia as the flows gets to the steady state earlier than the case for the full sample, whilst for Kenya and South Africa the effects largely mimic that of the full sample. In all three cases, the results suggest that the effect of shocks to inflows after the structural break is equally anti-persistent.

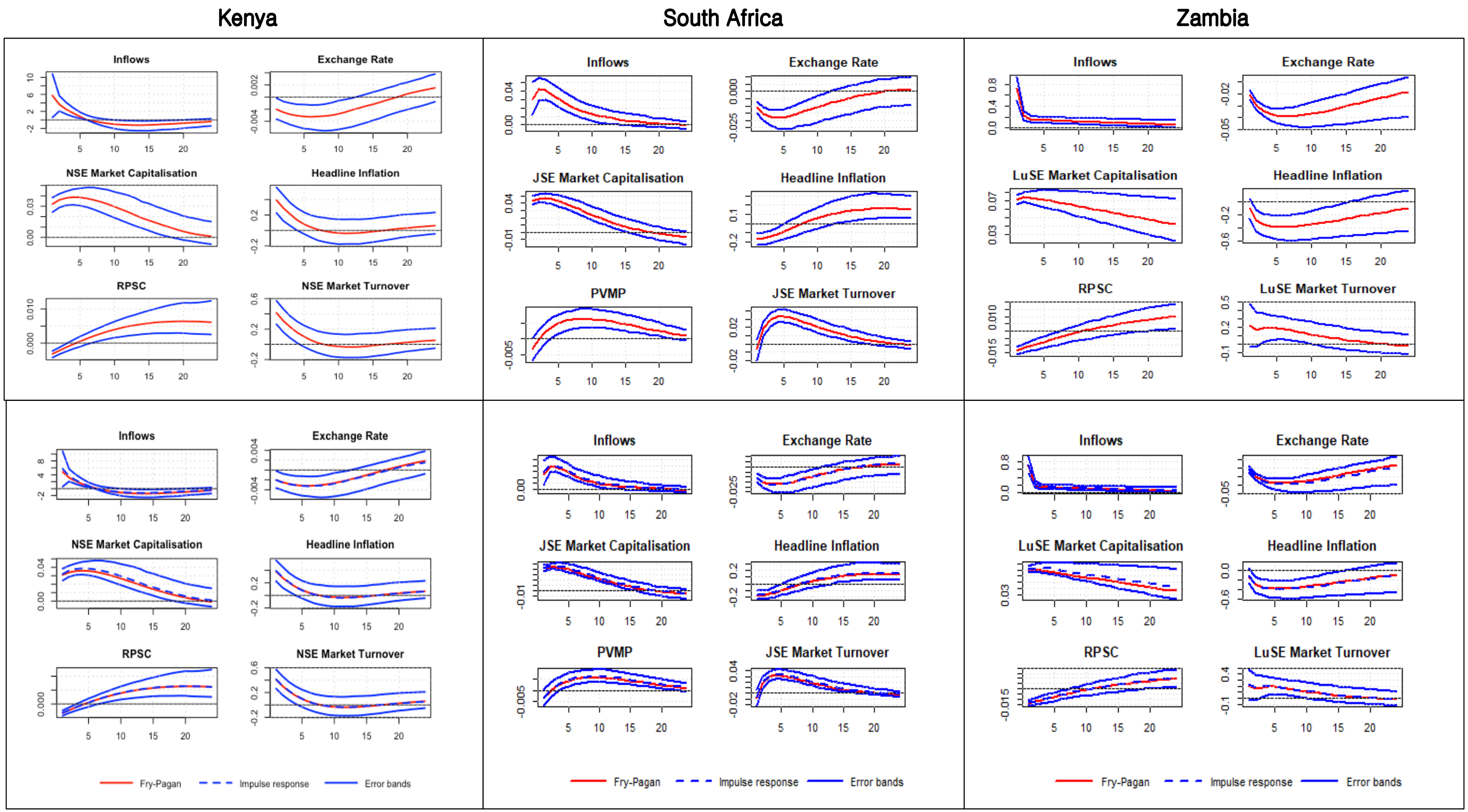
It appears that the gross foreign portfolio equity inflows to the four SSA countries may have similar underlying process as the inflows to a number of Asian and Latin American countries, as studied by Cai et al. (2016), Becker and Noone (2009), Sarno and Taylor (1999a), and Sarno and Taylor (1999b). This probably suggests that gross FPEI could be anti-persistent in nature for the emerging and frontier market economies.



Source: Author, Output from Studio R using VarSign Package

Note: Top panel is the Uhlig (2005) penalty function estimation results while the bottom panel has the Fry and Pagan (2011) Median – Target empirical results

Figure 5.1a: Impact of Shocks to Inflows on Stock Market Capitalisation – Full Sample



Note: Top panel is the Uhlig (2005) penalty function estimations and the bottom panel is for the Fry and Pagan (2011) Median – Target results
Source: Author, Output from Studio R using VarSign Package

Figure 5.1b: Impact of Shocks to Inflows on Stock Market Capitalisation - After the Structural Break

In line with theory and empirical findings elsewhere on a positive relationship between capital inflows and stock market capitalisation (see for example, Yartey, 2010), the results in this study also show that a positive shock to the gross foreign portfolio equity inflows lead to a rise in stock market capitalisation (middle left graph for each country). The increase in foreign portfolio equity inflows therefore renders support to stock market development in the four SSA countries. The rise in the SSA stock markets capitalisation may partly be owing to the rise in market turnovers (bottom right in each case). An increase in the portfolio equity inflows is likely to induce demand for shares in the market, leading to a rise in share prices, owing to the rise in liquidity given the increase in market turnover.

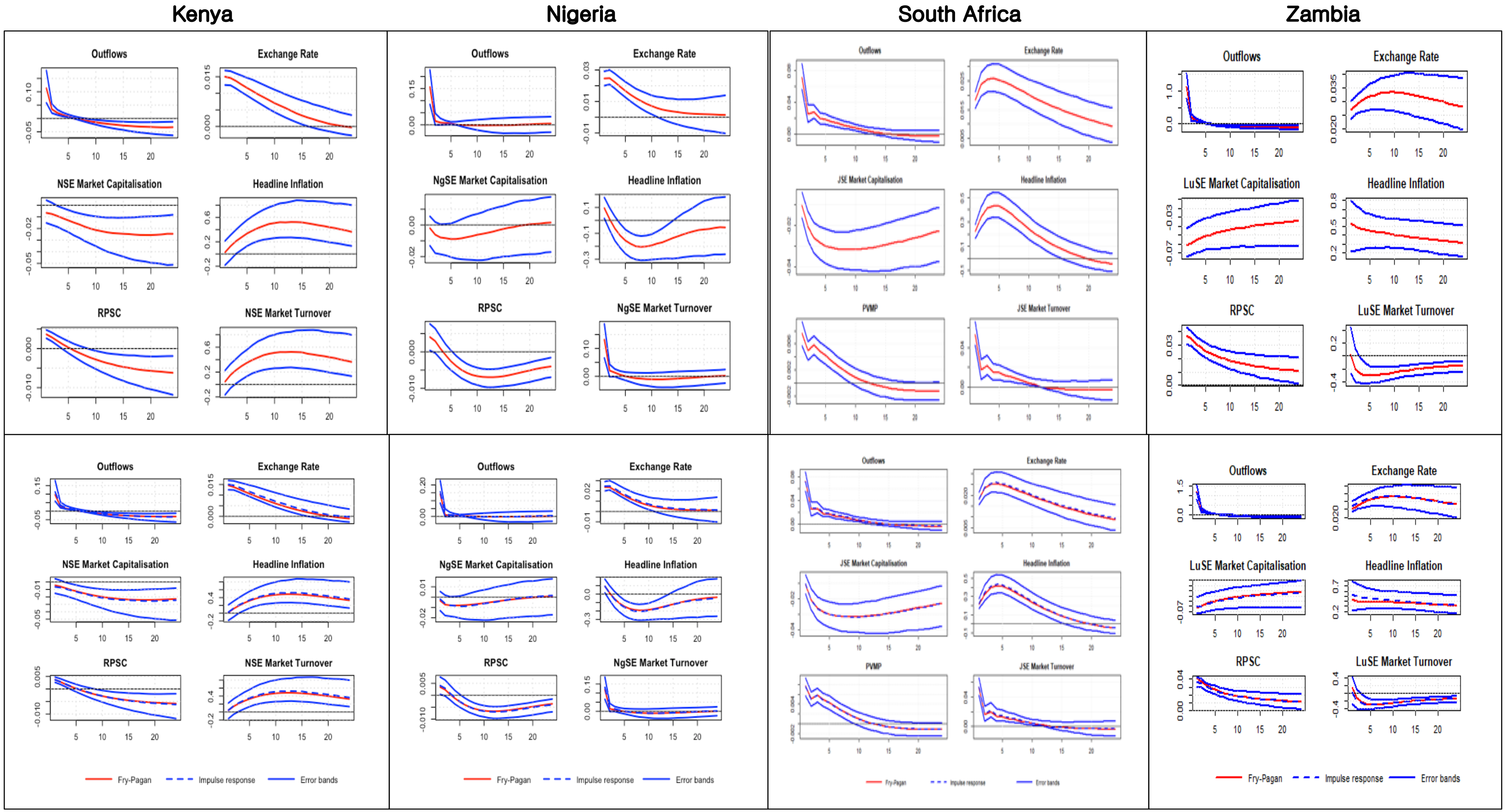
Specifically, in the case of Kenya, a shock to the foreign portfolio equity inflows causes a contemporaneous increase in market capitalisation, and it rises for five consecutive months after the structural break. This is longer than the three consecutive months increase related to the overall sample's estimates. The rise in market capitalisation for South Africa is continuous up to the fourth month under the full sample. However, the JSE market capitalisation rise is modest and lasts for about three months in the post structural break era, consistent with a relatively low increase in market turnover. Regarding Zambia's LuSE market capitalisation under the full sample, there is a contemporaneous increase following a positive shock to the foreign portfolio equity inflows, but the effect of the shock subsequently declines after the first month. Market capitalisation, however, increases for two consecutive months in the period after the structural break. Nigeria's stock market capitalisation increases for about five consecutive months before the shock effects begin to decline.

The magnitude of the impact is the smallest in the case of South Africa, suggesting that the foreign portfolio equity inflows to South Africa may be smaller as a percentage of the JSE market capitalisation in comparison with the other three countries in this study. This could be because of the larger size of the JSE in terms of market capitalisation and number of listings, and hence diversification opportunities and greater liquidity. This makes it comparatively more attractive to domestic investors as well. South Africa's economy and financial markets are relatively deeper and more diversified than the economies of other SSA countries (Calderón and Kubota, 2018). This contrasts with the LuSE on the other extreme, which only has 23 listed companies (as at the end of December 2019), and which recorded the biggest magnitude of the shock impact.

For the rest of the variables in the estimated extended *Calderon-Rossell* model for each country, the transmission mechanism that plays out is that a shock to the inflows leads to the appreciation of the exchange rate (top right graph in each case) resulting in inflation falling (middle right graphs). Real economic activity (bottom left), as proxied by RPSC (Kenya, Nigeria and Zambia) declines on impact (either for the full sample or for the period after the structural breaks), but then recovers subsequently. However, real economic activity for South Africa (proxied by PVMP) slows down on impact from the shock to the inflows, and this induces some volatility, but gets to the steady state in the fourth month (bottom left). Perhaps the slowdown responds to the appreciation of the Rand, leading to export demand slowing down as exports become expensive to foreign buyers of locally manufactured goods. After the structural break, the response of PVMP is the same as for the other three countries.

For confirmation of sturdiness of the obtained results, the Fry and Pagan (2011) MT method's estimates show the estimation outcomes above to be robust, as there is convergence in the results given the clear lack of divergence in the two estimates (solid red lines and dotted blue lines, lower panel of Figures 6.1a and 6.1b). In addition, the MCMC results for the posterior draws used in constructing the impulse responses due to the shock to foreign portfolio equity inflows had minimal rejections in some cases, and none in others. The results can therefore be relied upon.

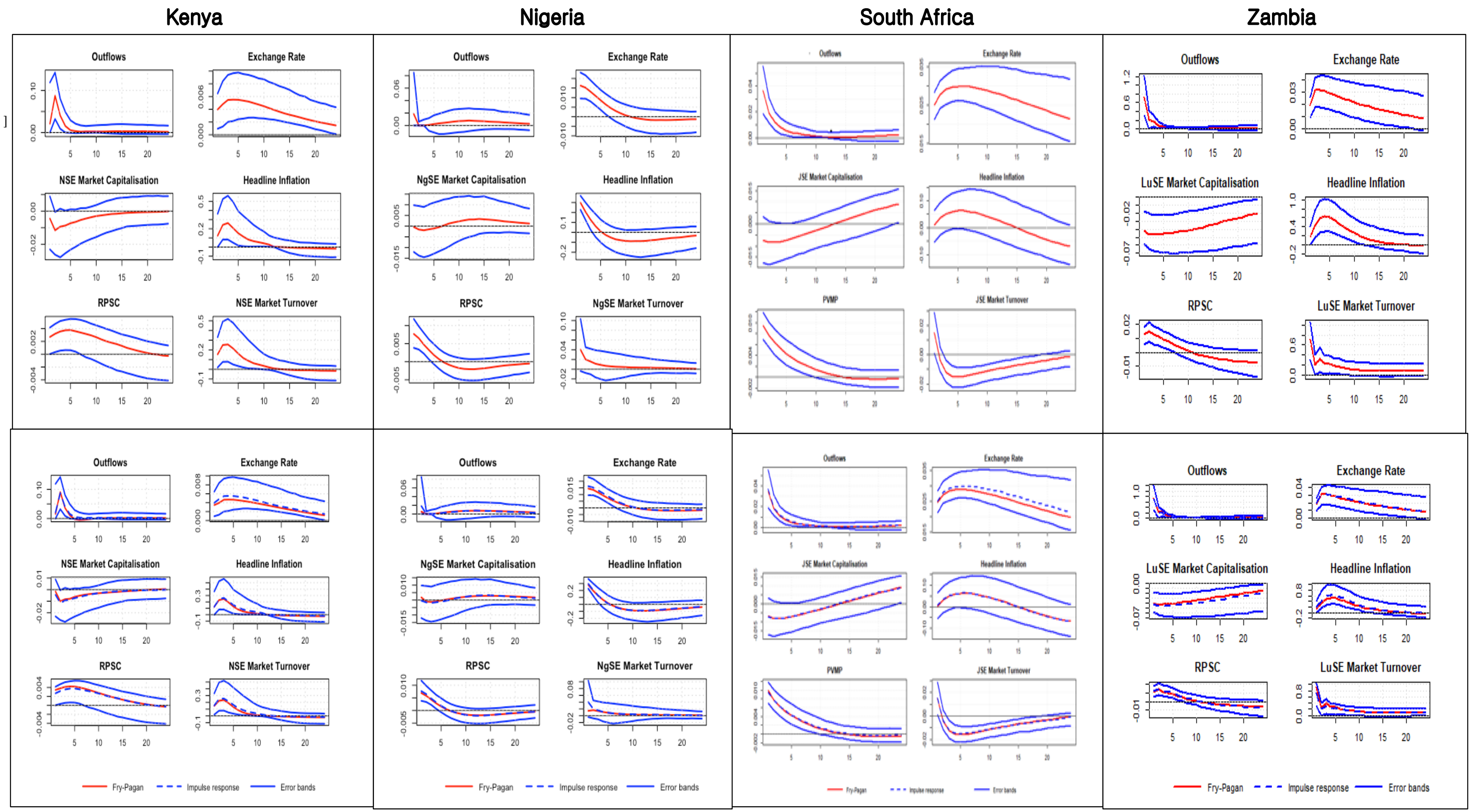
Turning to the effect of the shock on the foreign portfolio equity outflows on market capitalisation and the rest of the variables within the *Calderon-Rossell* framework, the results, in line with the shock identification scheme, indicate that a positive shock to the foreign portfolio equity outflows leads to an increase of the outflows (top left graphs, Figures 5.2a and 5.2b on the next page). This results in market capitalisations declining in all cases, both for the full samples and post-structural break sub-samples, (middle left graphs).



Source: Author, Output from Studio R using VarSign Package

Note: Top panel is the Uhlig (2005) penalty function results, and the bottom panel has the Fry and Pagan (2011) Median – Target results

Figure 5.2a: Impact of Shocks to Outflows on Stock Market Capitalisation – Full Sample



Source: Author, Output from Studio R using VarSign Package

Note: Top panel are the Uhlig (2005) penalty function estimations, and the bottom panel contains the Fry and Pagan (2011) Median – Target results

Figure 5.2b: Impact of Shocks to Outflows on Stock Market Capitalisation - After the Structural Break

The decline in market capitalisation could be due to a general decline in the value of transactions (market turnover) after the positive shock to the outflows. As noted from the literature, there is largely a positive relationship between market turnover and market capitalisation as postulated by the *Calderon-Rossell* model, and empirically verified, for example, by Sezgin and Atakan (2015), Yartey (2010), and el-Wassal (2005). Therefore, a broader negative effect on market turnover may lead to a decline in market capitalisation.

Although it was argued in the methodology section that market capitalisation may go either way (increase or decrease) following a positive shock to the foreign portfolio equity outflows, the empirical results indicate the effects to be largely of a declining nature for all the four countries. This is consistent with the mathematical proposition in Section 5.2. This empirical outcome may imply that in each of the four countries there is oversupply of the shares in the secondary market from foreign portfolio investors once there is a shock that leads to investors exiting the market. This may be associated with a tendency for *flight to safety* among these foreign portfolio investors in the four SSA countries. Thus, even if foreign portfolio investors seek high yields or returns, this may not be at the expense of the safety of such investments.

The behaviour of gross foreign portfolio equity outflows and market capitalisation for the respective countries' full samples vary in terms of the duration of the effect of the shocks. Thus, a shock to Kenya's gross FPEO leads to the outflows to increase on impact, but then fall in the second month and reach the steady state around the fourth month. This is different to South Africa, where the outflows rise on impact but then largely falls up to the 13th month to reach the steady state. In Zambia and Nigeria, the response is seemingly identical, with a shock to the respective gross foreign portfolio equity outflows resulting in the outflows increasing on impact but falling in the second month and reaching the steady state in the third month. The magnitude of the impact is highest for Zambia, and lowest for South Africa.

However, after the structural break, only the outflows associated with Nigeria reverse quickly after a shock, reaching the steady state in the second month. This notwithstanding, the magnitude of the effect of the shock to Nigeria's gross foreign portfolio equity outflows is the smallest among the four countries, followed by South

Africa. As argued in the previous chapter, this outcome could be related to the restrictions on foreign currency transactions imposed by the Nigerian government after the 2015 commodity price crisis, whilst for South Africa it may be due to bureaucratic requirements by the SARB on the transfer of funds from that country. As established by Ellyne and Chater (2016), Nigeria and South Africa have relatively more restrictions on their capital accounts than Zambia and Kenya, which probably explains the difference in the magnitude of the shock effects.

The results on the impact of shocks on the stock market capitalisation for each stock exchange for both the full and post- structural break samples were mixed. Only the NgSE's market capitalisation was found to converge to the steady state within the specified period of shock propagations for both the full and post-structural break samples. In fact, after the structural break, the impact seems minimal, and does not last long when compared to the effect under the full sample.

The JSE's market capitalisation declines on impact but shows signs of recovery after three months in the post structural break era and recovers fully by the 13th month. However, it does not get to the steady state immediately, but instead continues to increase and thus wipe out losses attained during the time of declining following a positive shock to the outflows. This could be in line with the recovery in its market turnover, possibly induced by rising demand or even supply of new shares by way of new listings, given that the JSE is regarded as the most active stock market in Africa.

The market capitalisation of Kenya's NSE only declines in the first two months and reaches the steady state by the 15th month in the post-structural break era. This contrasts with the behaviour exhibited under the full sample, where no convergence to the steady state is attained within the set horizon for impulse response functions. The market capitalisation of Zambia's LuSE, on the other hand, does not get to the steady state over the specified horizon, but it nonetheless shows signs of recovery after two months of consecutive decline. The sluggish movement of the LuSE's market capitalisation towards its steady state may be related to the fiscal slippage in Zambia that came to the fore in September 2013. The resulting fiscal imbalances have remained unresolved and the country's economic growth has slowed down, as a result, with real GDP growth averaging 3.6 percent over the period 2013-2019, down from the average of 6.5 percent recorded in the period 2006-2012. Over the period October 2013 to March 2020, the LuSE's market capitalisation in local currency grew by only 0.53 percent to 57.2 billion Zambian Kwacha, reflecting subdued economic activity induced by low liquidity as a result of a crowding out effect caused by increased government's domestic borrowing.

Following a positive shock to foreign portfolio outflows, the real economic activity, as represented by the PVMP (in case of South Africa) and RPSC (the other three countries), experience an increase in all the four countries (bottom left) but relatively modest for Zambia. The increase in economic activity may partly be due to a reaction to the exchange rate depreciation (top right), which may favourably contribute to the competitiveness of the exports of non-extractive products, and hence may induce an export-driven rise in respective countries' economic activity. An exchange rate depreciation may also contribute to an increase in inflation as the results show inflation rising (middle right).

The estimation on the gross foreign portfolio equity outflows, like the case for the inflows, also satisfy the Fry and Pagan (2011) MT method for *robustness*, given that the results convergence (solid red lines and dotted blue lines, lower panel of Figures 5.2a and 5.2b). Equally, the MCMC results for the posterior draws for constructing the impulse responses are satisfactory. The results can thus be relied upon.

Just as was the case with the gross foreign portfolio equity inflows, the effect of the shocks to the gross outflows in all four countries for all sample periods are found largely to be non-persistent. Further, the outflows in each case reach the steady state in a shorter period than the case with the equivalent inflows when hit by shocks. This may auger well for stock market development, as the gross inflows have a relatively longer positive effect on market capitalisation compared to the negative effect posed by shocks to gross outflows.

The net effects of these shocks on market capitalisation thus appear to be positive for the four SSA countries examined in this study, particularly in the period after the structural break ('the relevant past'). For example, the negative effect (defined as the time it takes to reach the steady state) of a shock to the outflows on the JSE's market capitalisation lasts about 12 months, with the greatest decline of 1.5 percent. However, for the same sub-sample the positive effect on the inflows causes an increase (although at a decreasing rate) over a period of 17 months following a shock, attaining a maximum increase of 4.0 percent. The same is true of Kenya, where the capitalisation of the NSE increases for nearly 24 months after a shock to inflows, compared to a declining effect of 14 months following a shock to the outflows. Further, in this case the rise in market capitalisation has a maximum of about 4.0 percent in response to a positive shock to the inflows while its decline is about 1.0 percent when there is a positive shock to the outflows.

The effects of the inflow and outflow shocks in the post-structural break period on the LuSE market capitalisation are longer-lasting than for South Africa and Kenya. However, as in the previous cases, the magnitude of the effect of inflow shocks on market capitalisation is again greater than that of outflow shocks (an increase of about 7.0 percent and decrease of about 4.0 percent, respectively).

Although the post-structural break was not estimated for Nigeria's FPEI for the reasons previously explained, it can, nonetheless, be argued that the full Nigerian sample period is so short that it can be seen as being equivalent to the post-structural break period for the other three countries in this study. On this basis, a comparison of the results between the inflows and the outflows full sample periods was undertaken. It was found that a shock to Nigeria's FPEIs result in an immediate increase of about 6.0 percent to the NgSE's market capitalisation and it continues to increase, peaking in the fifth month at about 8.0 percent above the starting level. Although the increasing trend slows down, the NGSE's market capitalisation does not reach the steady state over the set horizon. In the case of Nigeria's FPEOs, however, the decline in market capitalisation following a positive shock is only about 1.0 percent, realised in the fifth month. Thus, a shock to foreign portfolio equity inflows results in a relatively longer increase in market capitalisation, compared to the shorter duration of the effects of foreign portfolio equity outflows shock on the NgSE's market capitalisation.

The shorter duration of the effects of shocks on market capitalisation for the JSE and NSE (and the NgSE in respect of outflows) than for the LuSE in the post-structural break period may be related to the small size of Zambia's equity market compared to the other three countries. Although investors have opportunities to realise capital gains in a comparatively small but growing equity market like LuSE, the lack of diversification options on this exchange carries great risks in such a market. In this regard, limited options for investments at LuSE can make foreign investors move out of the equity market when conditions are unfavourable for the stocks under their holding and look elsewhere than switch to other stocks listed on the same exchange. The impact of that exit may have been reflected adversely on the LuSE's market capitalisation with some relatively long-lasting effect.

5.7. Implications of the Results

The results described in this chapter again underscores the need to account for structural breaks when undertaking empirical work intended to guide policy decisions. There is a definite difference in results for the full and post-structural break data sets. For example, the results for the full sample show a relatively long-lasting negative effect of the positive shock to foreign portfolio equity outflows on market capitalisation. However, for the data associated with the post structural break era, there is some convergence or recovery of market capitalisation to the steady state within a relatively shorter period following a positive shock to the outflows. Thus, it is necessary to take into account structural breaks if policy regrets are to be avoided, given that there is a fundamental difference in the results that ordinarily may require a different policy prescription if based on the results involving the sample without accounting for the structural break and one based on the period after the structural break.

Further, the results suggest, in view of the dichotomy of policy views on the management of capital flows, particularly in the context of foreign portfolio equity flows, that understanding their impact on stock market developments may be a useful input for policy considerations. Specifically, within the markets investigated, gross foreign portfolio equity inflows seem to have a relatively longer dynamic impact on stock market capitalisation compared to the gross foreign portfolio equity outflows. This suggests that these four SSA countries should focus on measures that attract more gross foreign portfolio equity inflows by continuing or improving procedures of enhancing capital account liberalisation. Focusing on policy measures that will attract more foreign portfolio equity inflows may enhance stock market liquidity and, in turn, stock market development, particularly for Kenya, Nigeria and Zambia, whose stock markets are not as developed as that of South Africa.

Additionally, Kenya, Nigeria and Zambia, may have to consider measures aimed at inducing the listing of shares from across many sectors. Multisectoral listing can help broaden the stock markets, which in turn may attract more foreign portfolio investors seeking broad based diversification within the market. This may consequently contribute to deepening these SSA stock markets.

The measures required to attract more foreign portfolio equity inflows are well documented in the literature on capital flow under the concept of pull-factors. However, these pull factors have been empirically found to account for a small portion of the foreign portfolio inflows in many developing countries (see for example Koepke, 2019; Sarno, Tsiakas and Ulloa, 2016; and Fernandez-Arias, 1996). Although this seem to suggest that the pull factors do not really play a significant role in attracting foreign portfolio equity inflows to developing countries, to the contrary it is probably an indictment on developing countries signifying that something needs to be done to the pull factors among the developing countries for such factors to help attract more foreign portfolio equity inflows. This is in line with the latest findings by IMF (2020) that domestic factors may matter in the way foreign portfolio equity flows behave. This, therefore, suggests that in the four SSA countries, perhaps, more especially Kenya, Nigeria and Zambia,[60] there is need to do more actions in making the elements of the pull factors attractive or effective to help improve the level of foreign portfolio inflows and limit their outflows, and therefore help develop their stock exchanges.

The pull factors include better economic performance, a sound general government primary balance, a greater degree of trade and financial account openness and stable exchange rates (Calderón and Kubota, 2018). In particular, Calderón and Kubota (2018) found a managed floating exchange rate to be a significant determinant of foreign portfolio equity inflows in SSA.

Although Calderon and Kubota (2018) did not explain why managed floating exchange rates may encourage foreign portfolio equity inflows, this could be due to foreign portfolio investors risk preferences. Thus, since foreign investors purchase assets

[60] These three countries have attracted inflows that are below the levels of inflows recorded in respect of South Africa.

denominated in local currency and thereby create a currency mismatch (Ibrahim Bah and Giritli, 2020), a depreciation in the exchange rate may erode their capital (in foreign currency terms through exchange losses). Therefore, on a currency risk adjusted basis, the investors may have a bias towards investing in countries with stable (or on the extreme, by extension, appreciating) exchange rates (Hu et al., 2016) in order to avoid exchange rate induced losses.

In view of this, building up foreign reserves should be, or continue to be, one of the priorities among these SSA countries, as this may assist in attracting more foreign portfolio equity inflows since this study has found these inflows to favourably impact stock market capitalisation in the four countries. The levels of foreign reserves may be an indicator to foreign portfolio investors of whether a country has sufficient US dollar (or any other reserve currency) liquidity to support an orderly exit from their investments in such a country. Foreign reserves, among other factors, are accumulated in order for the country to meet external obligations (Rule, 2015), which may include supporting an orderly exit from the domestic markets by foreign portfolio investors. Reserve adequacy may also help with stemming currency volatility (see for example Dominguez, Hashimoto, and Ito, 2011), which is another consideration of portfolio investors when making cross-border investment decisions. Countries with inadequate reserves may suffer more from the problem of *flight to safety* among foreign portfolio investors wanting to move to safe havens and thereby adversely affecting stock market capitalisation. Safe havens are countries whose currencies exhibit excess returns when global risks are heightened and when global liquidity conditions are tight (Goldberg and Krogstrup, 2019).

This study finds that foreign portfolio equity inflows cause stock market capitalisation to rise and thus contribute to the development of the stock exchanges for the countries under study. Thus, macroeconomic stability, which has largely been proxied by inflation in literature on the determinants of foreign portfolio investments (see for example Al-Smadi, 2018; Haider *et al.*, 2017; and Agarwal, 1997) should be another factor to manage by the four SSA countries, in order to attract more foreign portfolio equity inflows, and thereby help develop the stock markets of the four SSA countries studied. However, after the structural reforms of the 1990s, inflation is no longer a pervasive problem in several SSA countries (Nguyen et al., 2017), including the four sampled countries in this study. In this regard, macroeconomic stability for the SSA countries should be viewed in the context of fiscal balance, for example, as considered by Calderon and Kubota (2018). Nonetheless, the focus should be broader than just looking at the fiscal balance and, in this regard, authorities should rather consider the way fiscal operations are undertaken in order to attract more foreign portfolio equity inflows and thereby help develop the stock markets in particular the three countries of Kenya, Nigeria and Zambia that are less developed compared to South Africa's. This is in view of the results showing that foreign portfolio equity flows on a net basis may have a favorable impact on stock market capitalisation.

Fiscal operations in SSA have been overly pro-cyclical[61]. This is a problem in itself given that foreign portfolio equity flows, like other short-term foreign capital flows, largely are also procyclical in nature (see for instance Stiglitz, 2008). There is therefore need to orient fiscal operations towards counter-cyclical undertakings to aid macroeconomic stability and sustain economic growth in SSA, which are critical as pull factors. This matters in determining portfolio inflows and, by extension, stock market development. Although the issue of counter-cyclical fiscal operations may not be prominent in the literature on the determinants of FPEIs, its importance may not be inconsequential.

Foreign portfolio investors generally prefer to invest in countries with sound macroeconomic policies and management as they are sensitive to economic policies (Ahlquist, 2006). Therefore, countries pursuing counter cyclical fiscal operations may likely become more attractive to foreign portfolio investors. Based on the results of this study, this means that counter cyclical fiscal operations may help to avoid a boom-bust problem in foreign portfolio equity inflows, since they are pro-cyclical and may therefore contribute to a sustained rise in stock market capitalisation, holding other factors constant. Under a counter cyclical arrangement, there is less discretion (if any) with fiscal operations, as this is constrained by fiscal rules (Huang and Ho, 2020). In this regard, a build-up in fiscal imbalances may likely be minimised and their resolution can be relatively quicker, resulting in shorter periods of macroeconomic instability. It is the

[61] Irungu, Chevallier, and Ndiritu (2020); Ouedraogo and Sandrine (2018); Calderón, Chuhan-Pole and López-Monti (2017); and Tetsuya and Villafuerte (2016)

author's view that this is not just good for stock market development, but also for foreign portfolio equity inflows, which can lead to the two variables reinforcing each other.

For countries pursuing counter cyclical fiscal operations, exchange rates should be more stable, as demand for foreign currency by domestic economic agents may not be unusual under the resulting macroeconomic stability. Mordi (2006) has argued that restraint on money supply growth and prudent fiscal operations, factors supporting macroeconomic stability, reduces demand for foreign exchange. In the event of macroeconomic instability, domestic economic agents tend to demand more foreign assets to ensure capital preservation as evidenced by the tendency to seek safe havens (Goldberg and Krogstrup, 2019). The resulting greater demand for foreign exchange in the economy therefore puts pressure on the exchange rate, and the domestic currency depreciates. Given that foreign portfolio investors prefer to invest in markets with stable or appreciating exchange rates, as the case is with safe haven environments, this could help attract more foreign portfolio equity inflows to those countries with foreign exchange rate stability. In view of the results showing that foreign portfolio equity inflows contribute to the development of the stock exchanges of the four sampled countries in this study, these inflows could contribute to the rise in stock market capitalisation and therefore developing domestic stock markets in countries with prudent fiscal operations.

A stable macroeconomic environment may favourably affect corporate earnings as well. Foreign portfolio investors may target capital gains among the shares of listed firms, specifically if economic growth leads to favourable equity price valuations. Thus, achieving stable economic growth over time may help support stable growth in corporate earnings (although not in a linear way due to some frictions - see for example Khan, Nallareddy, and Rouen, 2016), and hence attract more foreign portfolio equity inflows. Favourable stock/share valuations may also emanate from the stable macroeconomic environment, arising from among other factors, the effects of counter-cyclical fiscal policies. In an unstable macroeconomic environment, risks are likely to be high and may therefore result in high funding costs or high cost of capital for the private sector (see for example, Corsetti et al., 2012). Conversely, macroeconomic stability may cause a decline in funding costs for firms, leading to a relatively low discount factor being applied to the valuation of anticipated dividends or free cash flows. Therefore, given the inverse relationship between the stock price and the discount factor, the valuation of equities is likely to increase in an environment of steady economic growth and stable macroeconomic conditions. This, intuitively, may appeal to foreign portfolio investors pursuing interests in markets with relatively low interest rates, as they seek capital gains. In this regard, De Santis and Lührmann (2009), in a panel study of over 73 countries across all the continents, found that in lower interest rate environments, more international investments were made in domestic stocks than domestic bonds.

In view of the above arguments, it is suggested that Nigeria and Zambia in particular need to reorient their fiscal policy towards counter cyclical operations, and there is also need to diversify the sources of fiscal revenue and export earnings. Currently the revenues and expenditures of these two countries are largely influenced by commodity prices, as their exports are dominated by oil and copper, respectively. A move towards counter cyclical operations can help attract more foreign portfolio equity inflows, and in turn will contribute to the further development of the Nigeria stock exchange and an up-lifting to the Lusaka securities exchange.

In literature it has been found that SSA countries that have a high degree of commodity export concentration like Nigeria and Zambia, are more inclined to pro-cyclical fiscal operations (Ouedraogo and Sandrine, 2018; and Tetsuya and Villafuerte, 2016). In addition, commodity price cyclicality has been established to have a positive relationship with the fluctuations in business cycles or economic growth of largely commodity exporting countries (Roch, 2019; and Polbin, Skrobotov and Zubarev, 2019). Therefore, the issue of counter cyclical fiscal operations for the two commodity exporting countries, Nigeria and Zambia, will help attract a steady flow of foreign portfolio equity inflows. This will not only help their stock markets capitalisation to rise but also avoid a boom-bust outcome that maybe associated with the procyclicality behaviour of the foreign portfolio equity inflows if domestic policies are also procyclical.

Specifically, in the case for Zambia, there is, in addition, a need to provide incentives for more corporate issuances if more foreign portfolio equity inflows are to be attracted, and also to allow the Lusaka securities exchange grow further in terms of market capitalisation, either in dollar terms or as a percentage of GDP. Elsewhere, including

Africa, Asia, Latin America and Europe, corporate issuances have been associated with foreign capital inflows (Calomiris, Larrain, and Schmukler, 2020).

Although South Africa is also a commodity exporting country, its exports are well diversified, and the country pursues a counter cyclical fiscal operation (Swanepoel and Schoeman, 2003). Its stock market is also well developed by global standards. The country should therefore focus on unlocking bottlenecks that have resulted in low economic growth by emerging market standards to boost its real GDP growth and thus sustain the foreign portfolio equity inflows into the country. Kenya's exports are also not dominated by a single product, and its economy is similarly fairly diversified (OECD/United Nations, 2011). However, with Kenya joining the club of oil producers and exporting countries, there is a risk that oil exports may eventually dominate its export receipts. This therefore poses a risk to Kenya as it may lose the diversification of its economy and exports if the revenues from the oil sector, once they become significant, do not go into supporting other sectors. Authorities in Kenya should therefore direct efforts towards improving and sustaining high broad based economic growth to attract more foreign portfolio equity inflows to grow the Nairobi Securities Exchange.

Attracting more foreign portfolio equity inflows in the four sub-Saharan Africa countries, particularly for Zambia, but also Kenya and Nigeria, may require some management, given the concerns highlighted in literature, such as volatility, *flight to safety* and sudden stop, among others. Capital controls as a capital flows management approach may not be an optimal policy action, as stock markets liquidity enhancement may be hindered due to restrictions on capital movements by capital control actions. This may thus hinder the development of the stock markets especially for Kenya, Nigeria, and Zambia. Financial or capital account liberalisation may be optimal for stock market development in these four countries and should thus be maintained or improved where necessary.

5.8. Chapter Summary

The empirical analysis described in this chapter investigated the impact of foreign portfolio equity flows (i.e., both in- and outflows) on the market capitalisation of the stock markets of Kenya, Nigeria, South Africa and Zambia. Bayesian VAR analysis with sign restriction was used to generate the impulse responses, which formed the basis for communicating and thus understanding how portfolio flow shocks affect these stock markets. The modified version of the *Calderon-Rossell* partial equilibrium model, as per Yartey (2008) and Yartey (2010), among others was estimated. For each country the estimation focused on the overall sample and a sub-sample covering the period after a structural break that was detected in each country's gross foreign portfolio equity inflows and outflows data. The macroeconomic approach to studying stock market capitalisation, as developed by Garcia and Liu (1999), was followed.

The results for the four countries indicate an increase in market capitalisation after a positive shock to gross foreign portfolio equity inflows, and a decline following a positive shock to gross foreign portfolio equity outflows. However, the magnitudes of these changes were different for the full sample periods compared to the post-structural break periods. Further, the declines resulting from shocks to FPEOs are lower than the increases resulting from positive shock to FPEIs. This could indicate the combined effects of positive shocks to gross foreign portfolio equity inflows and outflows may have a net positive effect on stock market capitalisation in the four SSA countries studied. Further, the positive shock to the gross foreign portfolio equity inflows and outflows although indicates a rise in each of the flows for both the overall sample and after the structural break, the behaviour of the two classes of FPEFs is anti-persistent in all cases.

The implication of these findings is that, since the gross foreign portfolio equity inflows and outflows are anti-persistent, their adverse impact on the stock markets in the four SSA countries is likely to be short lived following the shocks (e.g., a sudden stop for the case of inflows, and an unusual surge in the case of the outflows). Further, given that positive shocks to gross foreign portfolio equity inflows cause market capitalisation in each of the four countries to increase more than the declines in market capitalisation due to positive shocks to gross foreign portfolio equity outflows, the four countries should focus on creating the conditions that will attract more gross foreign portfolio equity inflows. This is to develop stock markets, particularly those in Kenya, Nigeria and Zambia, which are significantly less developed than that of South Africa.

Financial liberalisation could be an optimal policy option for the four SSA countries in view of the results obtained. The next chapter presents the conclusion and recommendations of this study, based on the empirical results established in Chapters 4 and the current Chapter. Additionally, it summarises their implications for capital control and financial liberalisation policies.

Chapter 6
Summary, Conclusion, Contribution, and Policy Implications

6.1. Introduction

This chapter summarises the findings of the two empirical chapters of this study and what they mean for theory and knowledge in general. It also discusses the implication of these findings on policy in light of the dichotomy of views on capital flows management. As indicated, one school of thought contends that capital controls are necessary to deal with the undesirable effects of foreign capital flows, whilst the other school argues that controls are not necessary, and that countries need to undertake or maintain financial liberalisation (also called capital account liberalisation) in order to benefit from foreign savings augmenting their domestic savings.

The argument made in this research is that a greater understanding of the underlying process of the foreign capital flows, and an understanding of the dynamic impact of the gross foreign portfolio equity flows on stock market development, may play a role in resolving the debate on this issue.

The findings of this study therefore contribute to the debate on whether capital controls or financial liberalisation are relevant in optimally influencing these flows, by utilising novel empirical approaches that include:

1) Estimating the underlying process of capital flows based on the Hurst parameter value using mono-fractal analysis that considers structural breaks in the data and the fractal signal classification. The latter technique, adopted from physiology, and electronic and communication engineering, helps to avoid misinterpreting the Hurst parameter, which is one of the measures of long-range dependence that portrays the underlying process of time series data;

2) Application of the *correlation measure,* a method not found in prior literature on foreign portfolio flows, to establish whether past or current events of portfolio equity flows have a bearing on the future occurrence of these flows. This reinforces the understanding of the underlying process of the foreign portfolio equity flows in the four SSA countries; and

3) Employing the Bayesian techniques with sign restrictions to estimate the *Calderon-Rossell* model (Calderon-Rossell, 1991 and 1990) in establishing the dynamic impact of shocks to gross foreign portfolio equity flows on stock market capitalisation within the *Calderon-Rossell* model. So far, this approach is lacking in literature on foreign portfolio equity flows. The sign restrictions are informed by the mathematical derivation in this work on the relationship between foreign portfolio equity flows and stock market capitalisation currently not available in literature, which is one of the contributions to theory emanating from this work.

To date, there is very limited empirical literature on the underlying process of foreign capital flows as well as their dynamic impact on stock market capitalisation. Even the literature that does exist on this has made minimal links to the management of these foreign portfolio equity flows.

In view of this problem, this thesis sought to provide answers to the following research questions that guided the study:

i. What is the underlying process of the gross foreign portfolio equity inflows and outflows data in a sample of the sub-Saharan African countries under investigation?

ii. How do past and current events of the foreign portfolio equity flows impact future events related to the foreign portfolio equity flows in these sub-Saharan African countries? What does that mean to further understand the underlying process of this class of foreign capital flows?

iii. How do shocks to foreign portfolio equity flows affect stock market capitalisation for Kenya, Nigeria, South Africa and Zambia, and how long do such impulses last in affecting the market capitalisation of the four selected sub-Saharan African equity markets?

iv. What policy insights can be drawn from the results and be applied as optimal policy interventions for each of the selected sub-Saharan African countries?

To provide answers to question (i), a fractal analysis technique based on the Detrended Fluctuation Analysis (DFA) was undertaken to compute the Hurst parameter. The robustness of the DFA results was assessed with the estimates from the Discrete Wavelet Analysis (DWA). Because the estimated Hurst parameter can have the same value for either the fBm or fGn signal, therefore, before undertaking the estimations, the data was subjected to fractal signal classification estimations.

In answering question (ii), a technique called *correlation measure*, which utilises the estimated Hurst coefficient value in the computation procedure, was used to determine whether past (or current) events associated with the gross foreign portfolio equity inflows and outflows have a bearing on the current (or future) outcomes of these flows. Estimation of the series convergence to respective long run steady states with speeds of adjustments (Beta convergence) were also considered given that these flows were established to be anti-persistent and by implication being mean reversion type of processes. This was to reinforce the understanding of their underlying process.

To address question (iii), a Bayesian technique with sign restrictions was employed to estimate the *Calderon-Rossell* partial equilibrium model, which is widely used in literature when empirically assessing factors affecting stock markets development. Sign restrictions are only available in Bayesian VAR methods, and the Bayesian technique was also adopted to overcome the challenges of undertaking empirical analysis on data with a short span, as the case is with most sub-Saharan Africa countries on foreign portfolio equity flow data.

6.2. Summary of Findings

The inference in this study is that the gross foreign portfolio equity inflows and foreign portfolio equity outflows associated with the four sub-Saharan Africa countries - Kenya, Nigeria, South Africa, and Zambia - have short memory. They are anti-persistent in terms of their underlying process. This means that these foreign portfolio equity flows have short range dependence. Therefore, this implies that a shock to these flows does not persist, and thus dies out in a relatively short period of time. This anti-persistent behaviour in respect of the four sub-Saharan Africa countries is confirmed by results from the signal classification, the Hurst parameter estimates, the *correlation measure*, and the Beta convergence estimation method.

The anti-persistent underlying process of foreign portfolio equity inflows and foreign portfolio equity outflows for Kenya, Nigeria, South Africa and Zambia is consistent with the findings of Bluedorn et al. (2013), Cai, Dang and Lai (2016), Levchenko and Mauro (2007), Sarno & Taylor (1999a) and Sarno & Taylor (1999b) elsewhere among Asian and Latin America countries, for example, although they all did not establish the speed of adjustment of these flows to their long run average. These flows are thus neither persistent nor of a random walk nature.

In addition, when there is a positive shock to the gross foreign portfolio equity inflows, the magnitude of the increase in market capitalisation is higher and the duration is relatively longer than the magnitude and duration in the fall in market capitalisation owing to the positive shocks to the outflows. Therefore, there is a likelihood for a positive gain in the stock markets for the four SSA countries owing to the dynamic effects of the foreign portfolio equity flows.

6.3. Conclusion and Contribution to Knowledge and Theory

The empirical estimates based on the fractal analysis for both the foreign portfolio equity inflows and outflows show each of these flows to be of short-range dependence for each country, which is largely consistent with the fractal signal classification estimates. This means that both foreign portfolio equity inflows and outflows associated with the four sub-Saharan Africa countries have an inherent stationary process and are therefore anti-persistent and not trend reinforcing. Thus, an increase in these flows in one period will be accompanied by a decrease in the flows in the next period and vice versa. The negative signs associated with each estimate in the *correlation measure* supports the conclusion that the effects of shocks to the flows in a particular direction in one period will in general be reversed in the subsequent period. Moreover, the Beta convergence estimates of the relevant parameter (all with negative signs) and the associated relatively high speed of convergence, especially in the period after respective structural breaks, confirms the mean reverting nature of these flows.

Further, the Bayesian techniques with sign restrictions show that a positive shock to both the gross foreign portfolio inflows and the outflows results in each of the two types of foreign portfolio equity flows for the four sub-Saharan Africa countries to rise, but their increase is not persistent. The inference from the Bayesian analysis also indicates that the positive shock to the gross foreign portfolio equity inflows leads to a rise in market capitalisation in the four sub-Saharan Africa countries that more than compensates for the decline in market capitalisation associated with a positive shock to the gross foreign portfolio equity outflows. This is true for both the overall sample and after the structural break, where applicable.

The work undertaken in this thesis makes the following contributions to the economics and finance literature in view of the results showing the foreign portfolio equity flows being anti-persistent, i.e. stationary, and may have a favourable impact on stock market capitalisation:

First, the study contributes to the economics and empirical finance literature on the stationarity or persistence in the variables by showing that data that may appear to have some persistence could be stationary when subjected to fractal signal classification tests. In this study this was shown for some variables displayed by either slowly decaying autocorrelation functions (ACF) or unit root tests suggesting an I(1) order of integration (Chapter 3), or by way of the estimated Hurst parameter (Chapter 4). In this regard, subjecting data to fractal signal classification can be a complementary action to the unit root tests commonly used in literature to establish whether economics or financial data is either stationary (akin to being an I(0) series) or persistent (analogous to an I(1) series). This suggestion is relevant to the issue of long-memory or fractional integration established among economics and financial variables[62]. The study therefore contributes to the literature on unit root tests and order of integration of time series data.

Second, this study contributes to existing empirical finance and economics literature on the use - perhaps more importantly on the interpretation - of the Hurst parameter. Thus, the application of fractal signal classification to the data to determine whether it is of the fBm or fGn signal can avoid a possible spurious interpretation, given that the Hurst parameter itself does not distinguish between the two types of signals. The fractal signal classification approach is scantly used in economics and empirical finance and, as to the

[62] See, for example, the works of Mensi, Tiwari and Al-Yahyaee (2019); Tarasov and Tarasova (2018); Wenger, Leschinski and Sibbertsen (2018); Ngene, Tah and Darrat (2017); Sensoy and Tabak (2015); Cajueiro and Tabak (2010); Couillard and Davison (2005); and Baillie (1996).

author's knowledge, not previously been employed in the literature on foreign capital flows, and on foreign portfolio equity flows in particular.

This work therefore also relates and contributes, by reiterating the concern put forward by Serinaldi (2010), among others, on the use and misuse of the Hurst parameter concerning stationary and non-stationary financial time series, to:

i. The empirical finance literature that is related to the Hurst exponent. One example is the efficient market hypothesis (EMH) or its variant – the random walk hypothesis (RWH) – that is assessed on the basis of the estimated Hurst parameter (see for example Onali and Goddard, 2011; Kristoufek and Vosvrda, 2013; Kang et al., 2014; Hiremath and Kattuman, 2017; Diallo and Mendy, 2019, and Mulligan, 2004). In the absence of knowledge of the fractal signal classification of the underlying data used to establish the EMH or RWH behaviour, the conclusion held may need to be revisited as a robustness check;

ii. The empirical finance literature involving the Hurst parameter on carry trade and other financial assets returns (see for example Lu, Li, Zhou and Qian, 2017; Auer and Hoffmann, 2016), trading rules/strategies for financial assets and commodities (see for example Auer, 2016a and Batten et al., 2013), and time-varying predictability of stock market returns and efficiency (such as Auer, 2016b; and Sensoy and Tabak, 2015). In view of the possibility of the data belonging to one of the two fractal signal classes (as confirmed by this study through the estimated β values and the visualisations done through simulations, both presented in Chapter 4), any future empirical work modelled along the works above or similar to such may have to interpret the Hurst parameter in light of the fractal signal classification of the underlying data. This will ensure the robustness of the conclusions made about the estimated Hurst parameter to maximise value from financial assets or commodities trading using trading strategies arising from the information on the Hurst coefficient generated by fractal analysis;

iii. The literature on the assessment of macroeconomic and financial variables based on the Hurst parameter values. For example, this may relate to empirical assessment such as monetary policy performance under different regimes (for instance Mulligan and Koppl, 2011; and Cajueiro and Tabak, 2010), foreign exchange rate behaviour (as for example by Kang et al., 2014; Pamu, Musongole, and Chokwe, 2012; and Corazza and Malliaris, 2002), term structure of interest rates (as by Cajueiro and Tabak, 2010; Cajueiro and Tabak, 2009; and Cajueiro and Tabak, 2007), and stock markets behaviour or correlations (as undertaken for example by Ferreira, Dionísio, and Movahed, 2017; Velasquez, 2010; Chimanga and Mlambo, 2014; Brooks et al., 2008; and Musongole, 2002). As stated before, incorporating information on fractal signal classification of the underlying data for this kind of empirical analysis may remove doubts on the validity of the interpretation of the results obtained; and

iv. The literature on forecasting economic and financial variables. An understanding of the underlying process of economic or financial variables as the case is with the foreign portfolio equity flows can help in anticipating the likely behaviour of these variables in terms of direction in the next episode once the initial conditions are established. For example, in the four SSA countries where the flows are found to be of the anti-persistent behaviour, it can be predicted that a rise in the flows in one period (if that is the initial condition at a particular time) will be accompanied by a decline in the flows in the next period. Conversely, if any of the series was found to be a persistent process, it can be anticipated that the series will rise further in the next episode if the initial condition shows the series to be rising. This kind of knowledge may be incorporated in forecasting the direction of not just the portfolio equity flows, but also other variables whose data may be subjected to fractal analysis that includes fractal signal classification. For example, if the underlying process of the data the forecaster is working with is anti-persistent, it will be reasonable for the forecaster to incorporate this information when imposing judgement on the future sample path of the values for a given variable i.e. the behaviour that the forecasted values may take, which should reasonably mimic the underlying behaviour, bearing in mind the possible structural change points/breaks. Therefore, knowledge of the underlying process considering the structural change points can reasonably play an important role in predicting or forecasting the future direction of many economic and financial variables.

Third, this work also relates to the literature on capital flows theory. With the results from this study suggesting that the underlying process of the flows from the four SSA countries are largely anti-persistent, in line with the empirical findings on foreign portfolio equity flows for some Latin American and Asian countries as established by Sarno and Taylor (1999a and 1999b) using state space methods, offers an opportunity to use fractal analysis and similar methods on many countries data on foreign capital flows to help develop theories on the underlying behaviour of not just the foreign portfolio equity flows, but also other classes of foreign capital flows. An understanding of the underlying behaviour of each class of foreign capital flows for many countries can help establish the general underlying behaviour of each class of capital flows. This will therefore contribute towards formulating a theory or theories on the underlying behaviour of foreign portfolio equity flows and other classes of foreign capital flows. The theory or theories may help with the optimal management of each class of foreign capital flows as opposed to applying a blanket capital flows management measure that may be sub-optimal to other classes;

Fourth, this work also relates to the literature on capital flows theory, but particularly on the impact of foreign capital flows on recipient countries. Whilst much has been written or mathematically derived on the likely impact of capital flows on economic growth of the recipient countries through particularly the Solow growth model (see for example Lorenzo and Miguel-Angel, 2000), little is formally or mathematically written on their impact on stock market development. The mathematical derivation done in this study provides formal support to modelling the postulated effect of foreign portfolio equity flows on stock market capitalisation, as this clearly shows the likely impact of foreign portfolio equity flows on stock market capitalisation. The derivation is based on domestic and foreign investors' stock market trading behavior, and in this regard the derivation is micro founded. In this regard it reinforces the postulation of a positive relationship between foreign capital flows and stock market capitalisation in the extended *Calderon-Rossell* model, as for example investigated in empirical work by el-Wassal (2005), Yartey (2008), Yartey (2010), Eniekezimene (2013) and Sezgin et al. (2015). Therefore, this work contributes towards developing a formal theory on gross foreign portfolio equity flows and stock market capitalisation by making a mathematical derivation on the relationship between foreign portfolio equity flows and stock market capitalisation currently not available in literature. The information from this derivation (the sign relationship between the two variables) was used to estimate the *Calderon-Rossell* model with Bayesian techniques for sign restrictions;

Fifth, the use of Bayesian methods with sign restrictions extends the scope for estimating the extended *Calderon-Rossell* model in a way that can help establish the dynamic effect of a shock to one of its determinants and to other variables within the system. This is achieved through the resulting impulse response functions, a procedure that, to the knowledge of the author, has not been applied to the estimation of the *Calderon-Rossell* partial equilibrium model before. Since economic variables interact as a system in such a way that a shock on one variable may affect others contemporaneously, but more often with a lag, this procedure is important to correctly visualise these interactions. This estimation approach can therefore enable researchers to understand the dynamic effect/impact of the shocks to variables in the system underpinned by the extended *Calderon-Rossell* model.

This study therefore extends the Bayesian Model Averaging work of Ng, Ibrahim and Mirakhor (2016) by instead employing Bayesian techniques with sign restrictions to estimate the *Calderon-Rossell* model (Calderon-Rossell, 1991 and 1990) in tracing how a shock to foreign portfolio equity flows propagates over time through an impulse response function, and also show how this shock affects stock market development via its market capitalisation. This is both in magnitude and direction (as is common in literature) as well as in time space, which is an improvement to the work by Ng, Ibrahim and Mirakhor (2016); and

Sixth, by having established that the gross foreign portfolio equity inflows and outflows associated with the four SSA countries have short memory and that their impact on stock markets capitalisation is favourable overall, this study underscores the need to avoid being influenced by the noise the time series data or events may be exhibiting at a particular time when considering investment options or policy interventions. As pointed out by Blanchard, L'Huillier and Lorenzoni (2013), noise play a critical part in short run dynamics and, depending on the severity of the noise, may lead investors (and policy makers alike, by extension) to have a wrong interpretation of the way events may unfold going forward. Therefore, the need to understand the nature of the underlying process of macro finance data and how it impacts other variables of interest is non-trivial in the optimisation of things related to value creation on a stock exchange or any investment field.

The inference in this study that the gross foreign portfolio equity inflows and foreign portfolio equity outflows associated with the four sub-Saharan Africa countries have short memory and that their impact on stock markets capitalisation is favourable overall, has implications on policy options as well. The section that follows discusses and provides policy recommendations considering the empirical findings.

6.4. Policy Recommendations

If the gross foreign portfolio equity inflows and outflows as per this study had been found to be persistent (i.e. had long-range dependence), it would be difficult at a given time to predict how long any undesirable behaviour of these flows may last, hence resulting in capital controls being a possibly viable option. Policy actions that transform the behaviour into one with short-range dependence (and thus anti-persistence) will be a possible solution, as this may require the use of market-based instruments to manage the flows thereafter. Equally, if the results of this study had suggested that these foreign portfolio equity flows belonged to (or followed) a random walk as an underlying process, imposing capital controls could also have been appropriate for the same reason: attempting to alter their behaviour so that they become more predictable. Thus, the core argument is that predictability is non-trivial in this context, as it can help with the management or control of such flows.

A process that is either long-range or short-range dependent is predictable, and this knowledge can give insight into how to manage the portfolio equity flows thereafter. Therefore, if the flows with a random walk behaviour are subjected to some measure of capital control, their behaviour may be altered into becoming a persistent process or an anti-persistent one. Assuming the behaviour is one that becomes a persistent process, further capital controls may be needed for the reason stated above (i.e., transforming its underlying behaviour into one that is anti-persistent).

However, the estimation outcome on the underlying process of the foreign portfolio equity flows in this study shows these flows to be anti-persistent, and their respective impact on stock markets shows the rise in market capitalisation due to shocks on the inflows to be higher than its fall due to a rise in the outflows. This implies that the imposition of capital controls as a way of controlling this particular class of foreign capital flows in these four countries is redundant, as these flows tend to self-correct. Financial liberalisation therefore appears to be the likely more optimal policy for the four sub-Saharan Africa countries, at least in the case of the foreign portfolio equity inflows and outflows.

In view of the empirical findings and given the polarised debate on whether capital controls should be applied to foreign capital flows, the findings in this study therefore suggest a rethink on the use of capital controls in the four investigated sub-Saharan Africa countries as a tool to manage foreign portfolio equity flows. The recommendation flowing from this study is therefore that capital controls may not be needed for this purpose, specifically because these flows are anti-persistent in behaviour, and the effect of shocks to these flows are not trend reinforcing. Thus, following a shock, these flows may deviate from their steady state for a while, but in most cases in less than six months, they revert to fluctuating around their long run average. Additionally, their impact on stock markets, although also not long-lasting, is such that overall, they favourably affect the market capitalisation of the four stock markets because the inflows cause larger increases in market capitalisation than the declines in market capitalisation at the hand of the outflows, either for the overall sample or under the respective countries' samples after the referenced structural breaks.

This therefore means that the respective countries in this study may benefit from capital account liberalisation for the foreign portfolio equity flows through its attendant benefits, as for example highlighted by Ellyne and Chater (2016). With this policy option, any undesirable behaviour of these flows could be dealt with by prudential actions and central bank foreign exchange interventions. Thus, capital account liberalisation policy options can be supported by other policy actions, being foreign exchange interventions by central banks through the purchase of foreign exchange, to build foreign reserves when there is a surge in the inflows, and the sale of foreign exchange during an unusual increase in the outflows to smoothen exchange rate volatility (Mumtaz *et al.*, 2014). Macroprudential policies may also be augmenting as an optimal policy undertaking in these countries since they are more effective at moderating foreign capital flows (including foreign portfolio equity flows; Zhang and Zoli, 2016) than capital controls (Bergant et al. 2020). This is especially so given that foreign capital flows are channeled through the banking system (Brunnermeier et al., 2012).

Regarding central bank interventions (Mumtaz *et al.*, 2014), this may limit the adverse impact of the outflows on some macroeconomic and financial variables, which is one of the major concerns related to increased foreign portfolio equity outflows when there is a domestic or global adverse shock. However, if foreign reserves are not adequate with regard to months of import cover, as the case currently is for the four countries, and are faced with mounting foreign debt, as in the case of Kenya and Zambia, maintaining an open capital account requires that the respective countries currencies must be flexible to accommodate the shock on the foreign equity portfolio outflows as per the IMF (2013) suggestion to Ghana, for example. In this regard, flexible exchange rate policy should accompany financial liberalisation policy on foreign portfolio equity flows in the four SSA countries.

On macroprudential measures, as established in literature by Bergant et al. (2020), they are more effective at moderating foreign capital flows in general than capital controls. Zhang and Zoli (2016) have further shown that this also applies to dealing with foreign portfolio equity flows. It is also established in literature that foreign capital flows are channeled through the banking system (see for example Brunnermeier et al., 2012), and therefore macroprudential actions may also help to manage these flows in that regard.

With financial liberalisation and an appropriate capital flows management framework in place by undertaking the suggested approaches above, the four sub-Saharan Africa countries should in addition strive to achieve and or maintain macroeconomic stability to attract more foreign portfolio equity inflows to support the development of their stock markets. Stable macroeconomic environments will not only ensure stable economic growth, but may also help corporate earnings growth which, although shown to be non-linear in the literature by Khan et al. (2016), may lead to favourable valuations for such firms. This in turn may help attract foreign portfolio investors seeking for capital gains. Their presence in these markets can augment liquidity, and thereby contribute to stock market development. Further, as these foreign portfolio flows are procyclical in nature, undertaking countercyclical fiscal policies can be attractive to foreign portfolio investors because of the stable macroeconomic environment such policy actions may likely deliver, and also in them preventing the boom-bust cycles these procyclical foreign portfolio flows are typically associated with.

6.5. Limitations of the Study and Possible Areas for Future Research

The irregular publication and general challenges of obtaining data on foreign portfolio equity flows among many sub-Saharan Africa countries made it difficult to broaden the coverage of countries in this study. In future, once more data of an appropriate frequency becomes available for more countries in this category, this work can be extended to other Sub-Saharan Africa countries, to assist in informing appropriate policy responses to foreign portfolio equity flows in the broader sub-Saharan African context.

Undertaking so many estimation procedures and communicating them all at once may risk the problem of comingled ideas. Therefore, the second possible area for additional research is an empirical assessment involving the establishment of the net contribution of foreign portfolio equity inflows and outflows on stock markets' capitalisation. One possible approach to undertaking this is the use of historical decomposition involving market capitalisation within the *Calderon-Rossell* framework using the difference between the individual contributions of the foreign portfolio equity inflows and outflows (*i.e.*, their net contribution).

Capital controls or financial liberalisation covers a broad class of capital flows and not just the foreign portfolio equity flows that are a focus of this study. In this regard, the third area for additional research may involve computing the signal classification and the ultimate computation of the Hurst parameter in respect of other classes of capital flows, such as foreign portfolio flows into Government securities for sub-Saharan Africa countries. This will broaden the understanding of the underlying process of other classes of capital flows, and thereby shed light on whether these flows may require an imposition of capital controls in managing them.

There is no theory on capital flow management, and this poses a challenge on the explicit policy action suitable for a particular class of foreign capital flows. Another possible area of research in this regard is the application of the fractal analysis alongside fractal signal classification to a broad class of gross foreign capital flows established in literature to be largely volatile for a broad set of countries beyond sub-Saharan Africa. This may help understand the broad underlying process of the different set of volatile gross foreign capital flows and assist in developing a theory or theories on the underlying behaviour of different classes of gross foreign capital flows.

Bibliography

Acharya, V. V, & Krishnamurthy, A. (2018). Capital Flow Management with Multiple Instruments. *NBER Working Paper Series*, (24443).

Adebowale, E. A., & Akosile, A. I. (2018). Interest Rate, Foreign Exchange Rate, and Stock Market Development in Nigeria. *Binus Business Review*, *9*(3), 247. https://doi.org/10.21512/bbr.v9i3.4941

Adeniyi, A. S. (2017). Exchange Rate Volatility and Stock Market Performance in Nigeria. *Asian Journal of Multidisciplinary Studies*, *5*(November 2017), 194–201.

Agarwal, R. N. (1997). Foreign Portfolio Investment In Some Developing Countries : A Study of Determinants and Macroeconomic Impact. *Indian Economic Review*, *32*(2), 217–229.

Ahlquist, J. S. (2006). Economic Policy, Institutions, and Capital Flows: Portfolio and Direct Investment Flows in Developing Countries. *International Studies Quarterly*, *50*(3), 681–704. https://doi.org/10.1111/j.1468-2478.2006.00420.x

Akhtaruzzaman, M., Hajzler, C., & Owen, P. D. (2018). Does Institutional Quality Resolve the Lucas Paradox? *Applied Economics*, *50*(5), 455–474. https://doi.org/10.1080/00036846.2017.1321840

Akileng, G., Ogwang, A. A., & Ssendyona, C. (2018). Determinants of Performance of Securities Exchanges in East Africa. *Journal of Finance and Investment Analysis*, *7*(3), 37–61.

Al-Smadi, M. O. (2018). Determinants of Foreign Portfolio Investment: The case of Jordan. *Investment Management and Financial Innovations*, *15*(1), 328–336. https://doi.org/10.21511/imfi.15(1).2018.27

Alfaro, L., Chari, A., & Kanczuk, F. (2017). The Real Effects of Capital Controls: Firm-Level Evidence from a Policy Experiment. *Journal of International Economics*, *108*, 191–210. https://doi.org/10.1016/j.jinteco.2017.06.004

Alfaro, L., Kalemli-Ozcan, S., & Volosovych, V. (2008). Why Doesn ' t Capital Flow from Rich to Poor Countries? An Empirical Investigation. *Review of Economics and Statistics*, *90*(2), 347–368.

Alley, I. (2017). Capital Flow Surges and Economic Growth in Sub-Saharan Africa: Any Role for Capital Controls ? *African Deevelopment Bank Working Paper Series*, (252).

Aluko, O. A., & Ibrahim, M. (2019). Does Institutional Quality Explain the Lucas Paradox ? Evidence from Africa. *Economics Bulletin*, *39*(3), 1687–1693.

Anand, Rahul, Ding, Ding, Peiris, S. J. (2011). Toward Inflation Targeting in Sri Lanka. *IMF Working Paper 11/81*.

Anaya, P., Hachula, M., & Offermanns, C. J. (2017). Spillovers of U.S. Unconventional Monetary Policy to Emerging Markets: The Role of Capital Flows. *Journal of International Money and Finance*, *73*, 275–295. https://doi.org/10.1016/j.jimonfin.2017.02.008

Andreasen, E., & Valenzuela, P. (2016). Financial Openness, Domestic Financial Development and Credit Ratings. *Finance Research Letters*, *16*, 11–18. https://doi.org/10.1016/j.frl.2015.10.019

Andrews, B. Y. D. W. K., & Ploberger, W. (1994). Optimal Tests when a Nuisance Parameter is Present Only Under the Alternative. *Econometrica*, *62*(6), 1383–1414. Retrieved from http://www.jstor.com/stable/2951753

Araujo, J. D., David, A. C., Hombeeck, C. Van, & Papageorgiou, C. (2015). Non-FDI Capital Inflows in Low-Income Developing Countries : Catching the Wave ? *IMF Working Papers, WP/15/86*.

Arias, J. E., Caldara, D., & Rubio-Ramírez, J. F. (2018). The Systematic Component of Monetary Policy in SVARs: An Agnostic Identification Procedure. *Journal of Monetary Economics*, *0*, 1–13. https://doi.org/10.1016/j.jmoneco.2018.07.011

Asiamah, M., Ofori, D., & Afful, J. (2019). Analysis of the Determinants of Foreign Direct Investment in Ghana. *Journal of Asian Business and Economic Studies*. https://doi.org/10.1108/jabes-08-2018-0057

Auer, Benjamin R. (2016a). On the Performance of Simple Trading Rules Derived from the Fractal Dynamics of Gold and Silver Price Fluctuations. *Finance Research Letters*, *16*, 255–267. https://doi.org/10.1016/j.frl.2015.12.009

Auer, Benjamin R. (2016b). On Time-Varying Predictability of Emerging Stock Market Returns. *Emerging Markets Review*, *27*, 1–13. https://doi.org/10.1016/j.ememar.2016.02.005

Auer, Benjamin R., & Hoffmann, A. (2016). Do Carry Trade Returns Show Signs of Long Memory? *Quarterly Review of Economics and Finance*, *61*, 201–208. https://doi.org/10.1016/j.qref.2016.02.007

Auer, Benjamin Rainer. (2018). Are Standard Asset Pricing Factors Long-Range Dependent? *Journal of Economics and Finance*. https://doi.org/10.1007/s12197-017-9385-y

Aysan, F. A., Fendoğlu, S., & Kilinc, M. (2015). Macroprudential Policies as Buffer Against Volatile Cross Border Capital Flows. *The Singapore Economic Review*, *60*(01).

Bacchetta, P., & van Wincoop, E. (1998). Capital Flows to Emerging Markets: Liberalisation, Overshooting, and Volatility,. *NBER Working Paper*, *WP 6530*.

Bai, B. Y. J., & Perron, P. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica*, *66*(1), 47–78.

Baillie, R. T. (1996). Long Memory Processes and Fractional Integration in Econometrics. *Journal of Econometrics*, *73*(1), 5–59. https://doi.org/10.1016/0304-4076(95)01732-1

Baillie, R. T. ., & Bollerslev, T. (1994). Cointegration , Fractional Cointegration , and Exchange Rate Dynamics. *The Journal of Finance*, *49*(2), 737–745.

Baillie, R. T., Calonaci, F., Cho, D., & Rho, S. (2019). Long Memory , Realized Volatility and HAR Models. *Queen Mary University of London, School of Economics and Finance Working Paper Series*, (881).

Baillie, R. T., & Wook, Y. (2019). Long Memory Volatility, Central Bank Intervention and Uncovered Interest Rate Parity in the 1920s Exchange Markets. *The Korean Economic Review*, *35*(1), 183–203.

Balakrishnan, R., Nowak, S., Panth, S., & Wu, Y. (2013). Surging Capital Flows To Emerging Asia: Facts, Impacts and Responses. *Journal of International Commerce,* *Economics and Policy*, *04*(02), 1350007. https://doi.org/10.1142/s1793993313500075

Balcerek, M., & Burnecki, K. (2020). Testing of Fractional Brownian Motion in a Noisy Environment. *Chaos, Solitons and Fractals*, *140*. https://doi.org/10.1016/j.chaos.2020.110097

Balta, N., & Vašíček, B. (2020). Financial Channels and Economic Activity in the Euro Area: A Large-Scale Bayesian VAR Approach. *Empirica*, *47*(2), 431–451. https://doi.org/10.1007/s10663-019-09432-x

Bańbura, M., Giannone, D., & Reichlin, L. (2010). Large Bayesian Vector Auto Regressions. *Journal of Applied Econometrics*, *25*(1), 71–92. https://doi.org/10.1002/jae.1137

Bank of Zambia. (2006). *Monetary Policy Statement*.

Batten, J. A., Ciner, C., Lucey, B. M., & Szilagyi, P. G. (2013). The Structure of Gold and Silver Spread Returns. *Quantitative Finance*, *13*(4), 561–570. https://doi.org/10.1080/14697688.2012.708777

Bayes, T., & Price, R. (1763). An Essay Towards Solving a Problem in the Doctrine of Chances. *Philosophical Transactions of the Royal Society of London*, (53), 370–418. https://doi.org/10.1365/s13291-013-0069-z

Becker, C., & Noone, C. (2009). Volatility and Persistence of Capital Flows. *Reserve Bank of Australia Research Discussion Paper (Sydney: Reserve Bank of Australia).*, *2009*(09). Retrieved from http://www.rba.gov.au/publications/rdp/2009/pdr/rdp2009-09.pdf.

Bekaert, G., & Harvey, C. R. (1997). Emerging Equity Market Volatility. *Journal of Financial Economics*, *43*(96), 29–77. https://doi.org/10.1111/j.1745-6584.2011.00876.x

Bekaert, G., & Harvey, C. R. (2003). Emerging Markets Finance. *Journal of Empirical Finance*, *10*(1–2), 3–55. https://doi.org/10.1016/S0927-5398(02)00054-3

Ben Zeev, N. (2017). Capital Controls as Shock Absorbers. *Journal of International Economics*, *109*, 43–67. https://doi.org/10.1016/j.jinteco.2017.08.004

Benbassat, G., Your, M., Visible, P., Serinaldi, F., Aldasoro, I., Unger, R., … Thompson, H. (2017). La Reconnaissance Automatique De La Parole. *Physica A: Statistical Mechanics and Its Applications*, *50*(3), 1–10. https://doi.org/10.1098/rstl.1763.0053

Benoit. (1999). BENOIT 1.31, TruSoft Int'l, Inc. Retrieved from http://www.trusoft.netmegs.com/.

Beran, J. (1992). Statistical Methods for Data with Long-Range Dependence. *Statistical Science*, *7*(4), 404–416.

Bergant, K., Grigoli, F., Hansen, N.-J., & Sandri, D. (2020). Dampening Global Financial Shocks: Can Macroprudential Regulation Help (More than Capital Controls)? *IMF Working Paper Series (WP20/106)*.

Bernanke, B. S. (1986). Alternative Explanation of the Money-Income Correlation. In: Brunner, K., and Metzler, A. (Eds). In *Real Business Cycles, Real Exchange Rates, and Actual Policies. Carnegie-Rochester Conference Series on Public Policy* (pp. 69–73).

Berti, P., Regazzini, E., & Rigo, P. (1991). Coherent Statistical Inference and Bayes Theorem. *The Annals of Statistics*, *19*(1), 366–381.

Bhatia, A., & Sharma, H. R. (2019). Financial Liberalization and Channels of Growth: A Comparative Study of Developed and Emerging Economies. *Indian Economic Review*. https://doi.org/10.1007/s41775-019-00038-5

Bhatt, S. J., Dedania, H. V., & Shah, V. R. (2016). Fractal Dimensional Analysis in Financial Time Series. *International Journal of Financial Management*, *5*(3). https://doi.org/10.21863/ijfm/2015.5.3.016

Bildirici, M. E. (2013). The Analysis of Relationship between Economic Growh and Electricity Consumption in Africa by ARDL Method. *ENERGY ECONOMICS LETTERS*, *1*(1), 1–14. Retrieved from http://www.aessweb.com/pdf-files/EEl 1(1), 1-14..pdf

Blanchard, Olivier J, L'Huillier, J.-P., & Lorenzoni, G. (2013). News, Noise, and Fluctuations: An Empirical Exploration. *The American Economic Review.*, *103*(7), 3045–3070.

Blanchard, Olivier Jean, & Quah, D. (1989). The Dynamic Effects of Aggregate Demand and Supply Disturbances. *American Economic Review*. https://doi.org/10.1016/S0164-0704(99)00102-0

Bluedorn, J. C., Duttagupta, R., Guajardo, J., & Topalova, P. (2013). Capital Flows Are Fickle: Anytime, Anywhere. *IMF Working Papers*, *WP/13/183*. https://doi.org/10.5089/9781484389041.001

Boako, G., & Alagidede, P. (2018). African Stock Markets in the Midst of the Global Financial Crisis: Recoupling or Decoupling? *Research in International Business and Finance*, *46*(December 2017), 166–180. https://doi.org/10.1016/j.ribaf.2018.02.001

Boero, G., Mandalinci, Z., & Taylor, M. P. (2019). Modelling Portfolio Capital Flows in a Global Framework: Multilateral Implications of Capital Controls. *Journal of International Money and Finance*, *90*, 142–160. https://doi.org/10.1016/j.jimonfin.2018.09.006

Brei, M., & Moreno, R. (2019). Reserve Requirements and Capital Flows in Latin America. *Journal of International Money and Finance*, *99*(741). https://doi.org/10.1016/j.jimonfin.2019.102079

Breidt, J. F., Crato, N., & Lima, P. De. (1998). On the Detection and Estimation of Long Memory in Stochastic Volatility. *Journal of Econometrics*, *83*(1–2), 325–348. https://doi.org/10.1016/S0304-4076(97)00072-9

Broner, F. A., & Rigobon, R. (2006). Why are Capital Flows so Much More Volatile in Emerging than in Developed Countries? In *External Vulnerability and Preventive Policies, ed. by Ricardo Caballero, César Calderón, and Luis Céspedes (Santiago: Central Bank of Chile).*

Broner, F., Didier, T., Erce, A., & Schmukler, S. L. (2013). Gross Capital Flows: Dynamics and Crises. *Journal of Monetary Economics*, *60*(1), 113–133. https://doi.org/10.1016/j.jmoneco.2012.12.004

Broner, F., & Rigobon, R. (2006). *Why are Capital Flows so Much More Volatile in Emerging than in Developed Countries? Ssrn*. https://doi.org/10.2139/ssrn.884381

Brooks, R. D., Maharaj, E. A., & Pellegrini, B. (2008). Estimation and Analysis of the Hurst Exponent for Australian Stocks Using Wavelet Analysis. *Applied Financial Economics Letters*, *4*(1), 41–44. https://doi.org/10.1080/17446540701367444

Brooks, R., Edison, H., Kumar, M. S., & Sløk, T. (2004). Exchange Rates and Capital Flows. *European Financial Management*, *10*(3), 511–533. https://doi.org/10.1111/j.1354-7798.2004.00261.x

Brunnermeier, M., Gregorio, J. De, Eichengreen, B., El-Erian, M., Fraga, A., Ito, T., … Yu, Y. (2012). Banks and Cross-Border Capital Flows: Policy Challenges and Regulatory Responses. *Committee on International Economic Policy and Reform*, *September*. Retrieved from http://wwwha.tcd.ie/policy-institute/assets/pdf/CIEPR_Lane_Presentation.pdf%5Cnhttp://localhost:8800/doku.php?id=brookingsinst2010

Bruno, V., Shim, I., & Shin, H. S. (2017). Comparative Assessment of Macroprudential Policies. *Journal of Financial Stability*, *28*, 183–202. https://doi.org/10.1016/j.jfs.2016.04.001

Bumann, S., & Lensink, R. (2016). Capital Account Liberalization and Income Inequality. *Journal of International Money and Finance*, *61*, 143–162. https://doi.org/10.1016/j.jimonfin.2015.10.004

Busch, U., Scharnagl, M., & Scheithauer, J. (2010). Loan Supply in Germany During the Financial Crisis. *Discussion Paper Series 1: Economic Studies*, (05), 1–40.

Byrne, J. P., & Fiess, N. (2016). International Capital Flows to Emerging Markets: National and Global Determinants. *Journal of International Money and Finance*, *61*, 82–100. https://doi.org/10.1016/j.jimonfin.2015.11.005

Cai, T., Dang, V. Q. T., & Lai, J. T. (2016). China's Capital and 'Hot' Money Flows: An Empirical Investigation. *Pacific Economic Review.*, *21*(3).

Cajueiro, D. O., Gogas, P., & Tabak, B. M. (2009). Does Financial Market Liberalization Increase the Degree of Market Efficiency ? The Case of the Athens Stock Exchange. *International Review of Financial Analysis*, *18*(1–2), 50–57. https://doi.org/10.1016/j.irfa.2008.11.004

Cajueiro, D. O., & Tabak, B. M. (2007). Time-Varying Long-Range Dependence in US Interest Rates. *Chaos, Solitons and Fractals*, *34*(2), 360–367. https://doi.org/10.1016/j.chaos.2006.04.012

Cajueiro, D. O., & Tabak, B. M. (2009). Testing for Long-Range Dependence in the Brazilian Term Structure of Interest Rates. *Chaos, Solitons and Fractals*, *40*(4), 1559–1573. https://doi.org/10.1016/j.chaos.2007.09.054

Cajueiro, D. O., & Tabak, B. M. (2010). Fluctuation Dynamics in US Interest Rates and the Role of Monetary Policy. *Finance Research Letters*, *7*(3), 163–169. https://doi.org/10.1016/j.frl.2010.03.001

Calderon-Rossell, R. (1991). The Determinants of Stock Market Growth. In G. S. Rhee & R. P. Chang (Eds.), *Pacific Basin Capital Markets Research Proceeding of The Second Annual Pacific Basin Finance Conference, 2, 4–6 June, Bangkok, Thailand.*

Calderón-Rossell, R. J. (1990). The Structure and Evolution of World Stock Markets. In *In: Rhee, S.G., Rosita, P.C. (Eds.), Pacific Basin Capital Markets Research Proceeding of* *the First Annual Pacific Basin Finance Conference. Elsevier Science Publishers B.V., Amsterdam.*

Calderón-Rossell, R. J. (1991). The Determinants of Stock Market Growth: A Worldwide Perspective. In *In: Rhee, S.G., Rosita, P.C. (Eds.), Pacific Basin Capital Markets Research Proceeding of the Second Annual Pacific Basin Finance Conference. Elsevier Science Publishers B.V., Amsterdam* (pp. 523–547).

Calderón, C., Chuhan-Pole, P., & López-Monti, R. M. (2017). *Cyclicality of Fiscal Policy in Sub-Saharan Africa Magnitude and Evolution* (No. 8108). Washington DC.

Calderón, C., & Kubota, M. (2018). International Financial Flows to Sub-Saharan Africa. In S. Gain (Ed.), *Africa's Pulse: An Analysis of issues shaping Africa's economic future* (Vol. 18). World Bank Group. Retrieved from http://documents.worldbank.org/curated/en/881211538485130572/pdf/130414-PUBLIC-WB-AfricasPulse-Fall2018-vol18-Web.pdf

Calomiris, C. W., Larrain, M., & Schmukler, S. L. (2020). Capital Inflows, Equity Issuance Activity, and Corporate Investment. *Journal of Financial Intermediation*, (July), 100845. https://doi.org/10.1016/j.jfi.2019.100845

Calvo, G. A., & Mendoza, E. G. (2000). Contagion, Globalization, and the Volatility of Capital Flows. In *Capital Flows and the Emerging Economies: Theory, Evidence and Controversies* (Vol. NBER Book, pp. 15–41).

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (2007). *The Econometrics of Financial Markets*. *Pricnce Town University Press*.

Campion, M. K., & Neumann, R. M. (2004). Compositional Effects of Capital Controls: Evidence from Latin America. *North American Journal of Economics and Finance*, *15*(2), 161–178. https://doi.org/10.1016/j.najef.2003.11.004

Cannon, M. J., Percival, D. B., Caccia, D. C., Raymond, G. M., & Bassingthwaighte, J. B. (1997). Evaluating Scaled Windowed Variance Methods for Estimating the Hurst Coefficient of Time Series. *Physica A: Statistical Mechanics and Its Applications*, *241*(3–4), 606–626. https://doi.org/10.1016/S0378-4371(97)00252-5

Canova, F., & Nicoló, G. De. (2002). Monetary Disturbances Matter for Business Fluctuations in the G-7. *Journal of Monetary Economics*, *49*(6), 1131–1159. https://doi.org/10.1016/S0304-3932(02)00145-9

Caporale, G. M., & Gil-Alana, L. A. (2014). Fractional Integration and Cointegration in US Financial Time Series Data. *Empirical Economics*, *47*(4), 1389–1410. https://doi.org/10.1007/s00181-013-0780-8

Carlin, J. B., Dempster, A. P., & Jonas, A. B. (1985). On Models and Methods for Bayesian Time Series Analysis. *Journal of Econometrics*, *30*(1–2), 67–90. https://doi.org/10.1016/0304-4076(85)90132-0

Carriero, A., Clark, T. E., & Marcellino, M. (2015). Bayesian VARs: Specification Choices and Forecast Accuracy. *Journal of Applied Econometrics*. https://doi.org/10.1002/jae.2315

Cave, J., Chaudhuri, K., & Kumbhakar, S. C. (2019). Do Banking Sector and Stock Market Development Matter for Economic Growth? *Empirical Economics*, (0123456789). https://doi.org/10.1007/s00181-019-01692-7

Cerutti, E., Claessens, S., & Andrew, K. (2017). How Important is the Global Financial Cycle? Evidence from Capital Flows. *CEPR Discussion Paper Series*, *12075*(661).

Cerutti, E., Claessens, S., & Laeven, L. (2017). The Use and Effectiveness of Macroprudential Policies: New Evidence. *Journal of Financial Stability*, *28*, 203–224. https://doi.org/10.1016/j.jfs.2015.10.004

Cha, K. S., & Bae, J. H. (2011). Dynamic Impacts of High Oil Prices on the Bioethanol and Feedstock Markets. *Energy Policy*, *39*(2), 753–760. https://doi.org/10.1016/j.enpol.2010.10.049

Chadha, J. S., Corrado, L., & Sun, Q. (2010). Money and Liquidity Effects: Separating Demand from Supply. *Journal of Economic Dynamics and Control*, *34*(9), 1732–1747. https://doi.org/10.1016/j.jedc.2010.06.020

Chamoli, A., Ram Bansal, A., & Dimri, V. P. (2007). Wavelet and Rescaled Range Approach for the Hurst Coefficient for Short and Long Time Series. *Computers and Geosciences*, *33*(1), 83–93. https://doi.org/10.1016/j.cageo.2006.05.008

Chamon, M., & Garcia, M. (2016). Capital Controls in Brazil: Effective? *Journal of International Money and Finance*, *61*, 163–187. https://doi.org/10.1016/j.jimonfin.2015.08.008

Chari, A., Henry, P. B., Chari, A., & Henry, P. B. (2004). Risk Sharing and Asset Prices: Evidence from a Natural Experiment. *Journal of Finance*, *59*(3), 1295–1324.

Chen, W. Den. (2006). Estimating the long memory granger causality effect with a spectrum estimator. *Journal of Forecasting*, *25*(3), 193–200. https://doi.org/10.1002/for.981

Chen, Y., Ding, M., & Kelso, J. (1997). Long Memory Processes (1/fα Type) in Human Coordination. *Physical Review Letters*, *79*, 4501–4504. https://doi.org/10.1103/PhysRevLett.79.4501

Chimanga, A., & Mlambo, C. (2014). The Fractal Nature of the Johannesburg Stock Exchange. *The African Finance Journal*, *16*(1), 39–57.

Chow, G. C. (1960). Tests of Equality Between Sets of Coefficients in Two Linear Regressions. *Econometrica*, *28*(3), 591–605. Retrieved from http://www.jstor.org/stable/1910133

Chukwuemeka, E. P., Stella, E. C., Victor, M., & Onyema, O. M. (2012). Modelling the Long Run Determinants of Foreign Portfolio Investment in an Emerging Market: Evidence From Nigeria. *Journal of Economics and Sustainable Development*, *3*(8), 194–205.

Churchill, R. Q., Arhenful, P., & Agbodohu, W. (2013). Stock Market and Economic Growth in Ghana. *Research Journal of Financial and Accounting*, *4*(2), 154–166. https://doi.org/10.5430/ijfr.v4n2p83

Claessens, S., Dooley, M. P., & Warner, A. (1995). Portfolio Capital Flows: Hot or Cold? *The World Bank Economic Review*, *9*(1), 153–174.

Corazza, M., & Malliaris, A. G. (2002). Multi-Fractality in Foreign Currency Markets. *Multinational Finance Journal*, *6*(2), 65–98. https://doi.org/10.17578/6-2-1

Corsetti, G., Kuester, K., Meier, A., & Mueller, J. G. (2012). Sovereign Risk, Fiscal Policy, and Macroeconomic Stability. *IMF Working Paper Series (WP12/33)*.

Couillard, M., & Davison, M. (2005). A Comment on Measuring the Hurst Exponent of Financial Time Series. *Physica A: Statistical Mechanics and Its Applications*, *348*, 404–418. https://doi.org/10.1016/j.physa.2004.09.035

Culha, A. (2006). A Structural VAR Analysis of the Determinants of Capital Flows Into Turkey. *Central Bank Review*, *6*(2), 11–35.

Curcuru, S. E., Thomas, C. P., Warnock, F. E., & Wongswan, J. (2011). U.S. International Equity Investment and Past and Prospective Returns. *NBER Working Paper Series*, (16677).

Danne, C. (2015). VARsignR: Estimating VARs Using Sign Restrictions in R. *Munich Personal RePEc Archive*, (68429). Retrieved from https://mpra.ub.uni-muenchen.de/68429/1/MPRA_paper_68429.pdf

Davidson, J. (2005). Testing for Fractional Cointegration: The Relationship Between Government Popularity and Economic Performance in the UK. *New Trends in Macroeconomics*, (March), 147–171. https://doi.org/10.1007/3-540-28556-3_8

Davis, J. S., Valente, G., & van Wincoop, E. (2019). Global Capital Flows Cycle: Impact on Gross and Net Flows. *National Bureau of Economic Research Working Paper Series, No. 25721*. https://doi.org/10.3386/w25721

De La Fuente, I. M., Perez-Samartin, A. L., Martínez, L., Garcia, M. A., & Vera-Lopez, A. (2006). Long-Range Correlations in Rabbit Brain Neural Activity. *Annals of Biomedical Engineering*, *34*(2), 295–299. https://doi.org/10.1007/s10439-005-9026-z

de Mello, L., & Pisu, M. (2010). The Bank Lending Channel of Monetary Transmission in Brazil: A VECM Approach. *Quarterly Review of Economics and Finance*, *50*(1), 50–60. https://doi.org/10.1016/j.qref.2009.09.006

de Menezes Barboza, R., & Vasconcelos, G. F. R. (2019). Measuring the Aggregate Effects of the Brazilian Development Bank on Investment. *North American Journal of Economics and Finance*, *47*(December 2018), 223–236. https://doi.org/10.1016/j.najef.2018.12.013

De Santis, R. A., & Lührmann, M. (2009). On the Determinants of Net International Portfolio Flows: A Global Perspective. *Journal of International Money and Finance*, *28*(5), 880–901. https://doi.org/10.1016/j.jimonfin.2008.09.002

De Vita, G., & Kyaw, K. S. (2008). Determinants of Capital Flows to Developing Countries: A Structural VAR Analysis. *Journal of Economic Studies*, *35*(4), 304–322. https://doi.org/10.1108/01443580810895608

Delignie, D. (2009). Fractal Dynamics of Human Gait : A Reassessment of the 1996 Data of Hausdorff et al ., 1272–1279. https://doi.org/10.1152/japplphysiol.90757.2008.

Delignieres, D., Ramdani, S., Lemoine, L., Torre, K., Fortes, M., & Ninot, G. (2006). Fractal Analyses for “Short” Time Series: A Re-Assessment of Classical Methods. *Journal of Mathematical Psychology*, *50*(6), 525–544. https://doi.org/10.1016/j.jmp.2006.07.004

Devereux, M. B., Young, E. R., & Yu, C. (2019). Capital Controls and Monetary Policy in Sudden-Stop Economies. *Journal of Monetary Economics*, *103*, 52–74. https://doi.org/10.1016/j.jmoneco.2018.07.016

Diallo, O. K., & Mendy, P. (2019). Wavelet Leader and Multifractal Detrended Fluctuation Analysis of Market Efficiency: Evidence from the WAEMU Market Index. *World Journal of Applied Economics*, *5*(1), 1–23. https://doi.org/10.22440/wjae.5.1.1

Dias, D. A., & Marques, C. R. (2010). Using Mean Reversion as a Measure of Persistence. *Economic Modelling*, *27*(1), 262–273. https://doi.org/10.1016/j.econmod.2009.09.006

Dima, B., & Dima, Ş. M. (2017). Mutual Information and Persistence in the Stochastic Volatility of Market Returns: An Emergent Market Example. *International Review of Economics and Finance*, *51*(May), 36–59. https://doi.org/10.1016/j.iref.2017.05.008

Doan, T., Litterman, R., & Sims, C. (1984). Forecasting and Conditional Projection Using Realistic Prior Distributions. *Econometric Reviews*. https://doi.org/10.1080/07474938408800053

Dominguez, K. M. E., Hashimoto, Y., & Ito, T. (2011). International Reserves and the Global Financial Crisis. *National Bureau of Economic Research Working Paper Series, No. 17362*. Retrieved from http://www.nber.org/papers/w17362%5Cnhttp://www.nber.org/papers/w17362

Donou-Adonsou, F. (2019). Colonialism Ties and Stock Markets: Evidence from Sub-Saharan Africa. *Research in International Business and Finance*. https://doi.org/10.1016/j.ribaf.2018.08.007

Dwyer, M. (1998). Impulse Response Priors for Discriminating Structural Vector Autoregressions. *UCLA Working Paper 780*. Retrieved from https://econwpa.ub.uni-muenchen.de/econ-wp/em/papers/9808/9808001.pdf

Edison, H. J., & Warnock, F. E. (2003). A Simple Measure of the Intensity of Capital Controls. *Journal of Empirical Finance*, *10*(1–2), 81–103. https://doi.org/10.1016/S0927-5398(02)00055-5

Edwards, S., & Rigobon, R. (2009). Capital Controls on Inflows, Exchange Rate Volatility and External Vulnerability. *Journal of International Economics*, *78*(2), 256–267. https://doi.org/10.1016/j.jinteco.2009.04.005

Eichengreen, B. (2001a). Capital Account Liberalization : What Do Cross-Country Studies Tell Us ? *The World Bank Economic Review*, *15*(3), 341–365.

Eichengreen, B. (2001b). Capital Account Liberalization : What Do Cross-Country Studies Tell Us? *The World Bank Economic Review*, *15*(3), 341–365. Retrieved from http://www.jsto.org/stable/3990106

Eichengreen, B., Gupta, P., & Masetti, O. (2017). Are Capital Flows Fickle? Increasingly? And Does the Answer Still Depend on Type? *World Bank Working Paper*, (February). https://doi.org/10.1162/asep_a_00583

Eichengreen, B., Gupta, P., Masetti, O., Neumann, R. M., Penl, R., Tanku, A., … Rajan, R. S. (2017). Do Capital Controls Make Gross Equity Flows to Emerging Markets Less Volatile? *Journal of International Money and Finance*, *18*(November 2015), 488–501. https://doi.org/10.1016/j.jmoneco.2012.12.004

Eke, A., Hermán, P., Bassingthwaighte, J. B., Raymond, G. M., Percival, D. B., Cannon, M., …

Ikrényi, C. (2000). Physiological Time Series: Distinguishing Fractal Noises from Motions. *Pflugers Archiv European Journal of Physiology*, *439*(4), 403–415. https://doi.org/10.1007/s004240050957

Eke, A., Herman, P., Kocsis, L., & Kozak, L. R. (2002). Fractal Characterization of Complexity in Temporal Physiological Signals. *Physiological Measurement*, *23*(1). https://doi.org/10.1088/0967-3334/23/1/201

el-Wassal, K. A. (2005). Understanding the Growth in Emerging Stock Markets. *Journal of Emerging Market Finance*, *4*(3), 227–261. https://doi.org/10.1177/097265270500400302

Ellyne, M., & Chater, R. (2016). A New Index for Measuring SADC Exchange Control Restrictiveness. *Review of Development Finance*, *6*(2), 139–150. https://doi.org/10.1016/j.rdf.2016.09.002

Enders, W. (2008). *Applied Econometric Time Series. John Wiley & Sons*. https://doi.org/10.1198/tech.2004.s813

Eniekezimene, F. A. (2013). The Impact of Foreign Portfolio Investment on Capital Market Growth : Evidence from Nigeria. *Global Business and Economics Research Journal*, *2*(8), 13–30.

Ergemen, Y. E. (2019). System Estimation of Panel Data Models Under Long-Range Dependence. *Journal of Business and Economic Statistics*, *37*(1), 13–26. https://doi.org/10.1080/07350015.2016.1255217

Ergemen, Y. E., & Velasco, C. (2017). Estimation of Fractionally Integrated Panels with Fixed Effects and Cross-Section Dependence. *Journal of Econometrics*, *196*(2), 248–258. https://doi.org/10.1016/j.jeconom.2016.05.020

Ewa, U. E., Adebisi, A. W., & Ijing, A. J. (2018). Perception on the Naira Devaluation and Iits Effects on Poverty. *European Journal of Accounting, Auditing and Finance Research*, *6*(5), 20–34. Retrieved from https://www.researchgate.net/publication/337171433_PERCEPTION_ON_THE_NAIRA_DEVALUATION_AND_ITS_EFFECTS_ON_POVERTY_REDUCTION_IN_NIGERIA/link/5dc9bd38458515143503bbd3/download

Faust, J. (1998). The Robustness of Identified VAR Conclusions About Money. *Carnegie-Rochester Conference Series on Public Policy*, *49*, 207–244. Retrieved from https://ac.els-cdn.com/S0167223199000093/1-s2.0-S0167223199000093-main.pdf?_tid=4d7966f4-3d0b-469f-a154-3d7e152a9b6e&acdnat=1539163979_40a736efe1b3f85cc470bdfc4e5fc475

Fedderke, J. W., & Liu, W. (2002). Modelling the Determinants of Capital Flows and Capital fFight: With an Application to South African Data from 1960 to 1995. *Economic Modelling*, *19*(3), 419–444. https://doi.org/10.1016/S0264-9993(01)00071-2

Feldstein, M., & Horioka, C. (1980). Domestic Saving and International Capital Flows. *Economic Journal*, *90*, 314–329.

Fernandez-Arias, E. (1996). The New Wave of Private Capital Inflows: Push or Pull? *Journal of Development Economics*, *48*(2), 389–418. https://doi.org/10.1016/0304-3878(95)00041-0

Fernández, A., Rebucci, A., & Uribe, M. (2015). Are Capital Controls Countercyclical? *Journal of Monetary Economics*, *76*, 1–14. https://doi.org/10.1016/j.jmoneco.2015.07.001

Fernandez, V. (2011). Alternative Estimators of Long-Range Dependence. *Studies in Nonlinear Dynamics and Econometrics*, *15*(2). https://doi.org/10.2202/1558-3708.1798

Ferreira, P., Dionísio, A., & Movahed, S. M. S. (2017). Assessment of 48 Stock Markets Using Adaptive Multifractal Approach. *Physica A: Statistical Mechanics and Its Applications*, *486*, 730–750. https://doi.org/10.1016/j.physa.2017.05.046

Fisher, L. A., & Huh, H. S. (2020). Combining sign and parametric restrictions in SVARs by utilising Givens rotations. *Studies in Nonlinear Dynamics and Econometrics*, *24*(3), 1–19. https://doi.org/10.1515/snde-2018-0104

Fisher, R. A. (1925). *Statistical methods for Research Workers*. *Oliver & Boyd*. https://doi.org/10.1056/NEJMc061160

Flint, E., & Maré, E. (2017). Fractional Black – Scholes Option Pricing , Volatility Calibration and Implied Hurst Exponents in South African Context. *South African Journal of Economic and Management Sciences*, *ISSN: (Onl*, 1–11.

Fofack, A. D., Aker, A., & Rjoub, H. (2020). Assessing the Post-Quantitative Easing Surge in Financial Flows to Developing and Emerging Market Economies. *Journal of Applied Economics*, *23*(1), 89–105. https://doi.org/10.1080/15140326.2019.1710421

Forbes, K., Chari, A., Dominguez, K., Frankel, J., Garcia, M., Ghosh, R., … Yetman, J. (2015). Capital Flow-Management Measures: What Are They For? *Journal of International Economics*, *96*(SI), 76–97.

Forbes, K. J., & Warnock, F. E. (2012a). Capital Flow Waves : Surges, Stops, Flight, and Retrenchment. *Journal of International Economics*, *88*(2), 235–251. https://doi.org/10.1016/j.jinteco.2012.03.006

Forbes, K. J., & Warnock, F. E. (2012b). Capital Flow Waves: Surges, Stops, Flight, and Retrenchment. *Journal of International Economics*, *88*(2), 235–251. https://doi.org/10.1016/j.jinteco.2012.03.006

Fratzscher, M., Juvenal, L., & Sarno, L. (2010). Asset Prices, Exchange Rates and the Current Account. *European Economic Review*, *54*(5), 643–658. https://doi.org/10.1016/j.euroecorev.2009.12.005

Fratzscher, M., & Straub, R. (2009). Asset Prices and Current Account Fluctuations in G-7 economies. *IMF Staff Papers*, *56*(3), 633–654. https://doi.org/10.1057/imfsp.2009.8

French, J. J. (2011). The Dynamic Interaction Between Foreign Equity Flows and Returns : Evidence From the Johannesburg Stock Exchange. *The International Journal of Business and Finance Research*, *5*(4), 45–56.

French, K. R., & Poterba, J. M. (1991). Investor Diversification and International Equity Markets. *The American Economic Review*. https://doi.org/10.1126/science.151.3712.867-a

Fry, R., & Pagan, A. (2011). Sign Restrictions in Structural Vector Autoregressions: A

Critical Review. *Journal of Economic Literature*, *49*(4), 938–960. https://doi.org/10.2139/ssrn.1668211

Furceri, D., & Loungani, P. (2018). The Distributional Effects of Capital Account Liberalization. *Journal of Development Economics*, *130*(November 2015), 127–144. https://doi.org/10.1016/j.jdeveco.2017.09.007

Gadanecz, B., & Jayaram, K. (2016). Macroprudential Policy Frameworks, Instruments and Indicators: A Review. *Bank for International Settlements*, *41*(December), 19. Retrieved from https://www.bis.org/ifc/publ/ifcb41c_rh.pdf

Galí, J. (1992). How Well Does the IS-LM Model Fit Postwar U.S. Data. *The Quarterly Journal of Economics*, *107*(2), 709–738.

Garcia, V., & Liu, L. (1999). Macroeconomic Determinants of Stock Market Development. *Journal of Applied Economics*, *II*(1), 29–59. https://doi.org/10.2139/ssrn.2773256

Garg, R., & Dua, P. (2014). Foreign Portfolio Investment Flows to India: Determinants and Analysis. *World Development*, *59*, 16–28. https://doi.org/10.1016/j.worlddev.2014.01.030

Gathenya, J. M. (2015). *Impact of Foreign Portfolio Equity Investments on the Market Capitalization of the Nairobi Securities Exchange (2004-2013)*. United States International University - Africa.

Ghosh, A. R., Ostry, J. D., & Qureshi, M. S. (2016). When Do Capital Inflow Surges End in Tears? *American Economic Review*, *106*(5), 581–585. https://doi.org/10.1257/aer.p20161015

Giannone, D., Lenza, M., Momferatou, D., & Onorante, L. (2014). Short-Term Inflation Projections: A Bayesian Vector Autoregressive Approach. *International Journal of Forecasting*, *30*(3), 635–644. https://doi.org/10.1016/j.ijforecast.2013.01.012

Giannone, D., Lenza, M., & Primiceri, G. (2015). Prior Selection for Vector Autoregressions. *Review of Economics and Statistics*, *97*(2), 436–451. https://doi.org/10.1016/j.csda.2016.02.011

Goldberg, L., & Krogstrup, S. (2019). International Capital Flow Pressures. *Federal Reserve Bank of New York Staff Reports*, (No. 834).

Gossel, S. J., & Biekpe, N. (2012). The Effects of Capital Inflows on South Africa's Economy. *Applied Financial Economics*, *22*(11), 923–938. https://doi.org/10.1080/09603107.2011.629982

Gourène, G. A. Z., Mendy, P., & N'gbo Ake, G. M. (2018). Multiple Time-Scales Analysis of Global Stock Markets Spillovers Effects in African Stock Markets. *International Economics*, *157*(September 2018), 82–98. https://doi.org/10.1016/j.inteco.2018.09.001

Gourinchas, P., & Jeanne, O. (2013). Capital Flows to Developing Countries : The Allocation Puzzle. *The Review of Economic Studies*, 1–32. https://doi.org/10.1093/restud/rdt004

Grabel, I. (2015). The Rebranding of Capital Controls in an Era of Productive Incoherence. *Review of International Political Economy*, *22*(1), 7–43. https://doi.org/10.1080/09692290.2013.836677

Granger, A. C. W. J. (1966). The Typical Spectral Shape of an Economic Variable.

Econometrica, *34*(1), 150–161.

Granziera, E., Moon, H. R., & Schorfheide, F. (2018). Inference for VARs Identified With Sign Restrictions. *Quantitative Economics*, *9*(3), 1087–1121. https://doi.org/10.3982/qe978

Grigorian, D. A. (2019). Nonresident Capital Flows and Volatility : Evidence from Malaysia ' s Local Currency Bond Market. *IMF - Working Paper*, *19*(23).

Guichard, S. (2017). Findings of the Recent Literature on International Capital Flows:Implications and Suggestions for Further Research. *OECD Economics Department Working Papers*, (1410, OECD Publishing, Paris). https://doi.org/10.1787/2f8e1d6d-en

Gyamfi, E. N., Kyei, K. A., & Gill, R. (2016). Long-Memory in Asset Returns and Volatility: Evidence from West Africa. *Investment Management and Financial Innovations*, *13*(2), 24–28. https://doi.org/10.21511/imfi.13(2).2016.03

Haider, M. A., Khan, M. A., Saddique, S., & Hashmi, S. H. (2017). The Impact of Stock Market Performance on Foreign Portfolio Investment in China. *International Journal of Economics and Financial Issues*, *7*(2), 460–468. https://doi.org/10.9790/487x-0241019

Hansen, B. E. (1992). Testing for Parameter Instability in Linear Models. *Journal of Policy Modeling*, *14*(4), 517–533.

Hansen, B. E. (2001). The New Econometrics of Structural Change: Dating Breaks in U. S. Labor Productivity. *The Journal of Economic Perspectives*, *15*(4), 117–128. Retrieved from http://www.jstor.com/stable/2696520

Harjes, T., & Ricci, L. A. (2010). A Bayesian-Estimated Model of Inflation Targeting in South Africa. *IMF Staff Papers*, *57*(2), 407–426. https://doi.org/10.1057/imfsp.2009.18

Hau, H., & Rey, H. (2004). Can Portfolio Rebalancing Explain the Dynamics of Equity Returns , Equity Flows , and Exchange Rates ? *The American Economic Review*, *94*(2), 126–133.

Hausdorff, J. M., Lertratanakul, A., Cudkowicz, M. E., Peterson, A. L., Kaliton, D., & Goldberger, A. L. (2000). Dynamic Markers of Altered Gait Rhythm in Amyotrophic Lateral Sclerosis. *Journal of Applied Physiology*, *88*(6), 2045–2053. https://doi.org/10.1152/jappl.2000.88.6.2045

Hegerty, S. W. (2020). Structural Breaks and Regional Inflation Convergence for Five New Euro Members. *Economic Change and Restructuring*, *53*(2), 219–239. https://doi.org/10.1007/s10644-018-9241-x

Heneghan, C., & McDarby, G. (2000). Establishing the Relation Between Detrended Fluctuation Analysis and Power Spectral Density Analysis for Stochastic Processes. *Physical Review E*, *62*(5), 6103–6110. https://doi.org/10.1103/PhysRevE.62.6103

Henry, P. B. (2003). Capital-Account Liberalization, the Cost of Capital, and Economic Growth. *The American Economic Review*, *93*(2), 91–96.

Hiremath, G. S., & Kattuman, P. (2017). Foreign Portfolio Flows and Emerging Stock Market : Is the Midnight Bell Ringing in India ? *Research in International Business and Finance*, *42*(April), 544–558. https://doi.org/10.1016/j.ribaf.2017.04.016

Hlivnjak, S. (2009). Current Account Convergence to the Long-Run Steady State for Bosnia and Herzegovina and the Western Balkans. In *Conference paper for Perugia, Italy* (pp. 1–36). Retrieved from http://www.stat.unipg.it/aissec2009/Documents/papers/Hlivnjak.pdf

Ho, S. Y. (2019). Macroeconomic Determinants of Stock Market Development in South Africa. *International Journal of Emerging Markets*, *14*(2), 322–342. https://doi.org/10.1108/IJoEM-09-2017-0341

Hristov, N., Hülsewig, O., & Wollmershäuser, T. (2012). Loan Supply Shocks During the Financial Crisis: Evidence for the Euro Area. *Journal of International Money and Finance*, *31*(3), 569–592. https://doi.org/10.1016/j.jimonfin.2011.10.007

Hu, M., Li, Y., Yang, J., & Chao, C. C. (2016). Actual Intervention and Verbal Intervention in the Chinese RMB Exchange Rate. *International Review of Economics and Finance*, *43*, 499–508. https://doi.org/10.1016/j.iref.2016.01.011

Huang, C.-J., & Ho, Y.-H. (2020). The Impact of Fiscal Rules on Economic Stabilization in Taiwan. *Nolegein Journal of Corporate & Business Laws*, *3*(1), 36–43.

Huang, Z., & You, Y. (2019). How Does Capital Control Spur Economic Growth? *World Economy*, *42*(4), 1234–1258. https://doi.org/10.1111/twec.12682

Hughes, D. (2006). *The Handbook of Asset Management Theory and Practice* (Indian Edi). New Delhi: Infinity Books, 203 Shivam Tower, Community Center, Paschim Vihar.

Hurst, H. E. (1951). Long-Term Storage Capacity of Reservoirs. *Transactions of the American Society of Civil Engineers*, *116*, 770–799. https://doi.org/10.1119/1.18629

Ibrahim Bah, S., & Giritli, N. (2020). What Drives Foreign Portfolio Investment Flows in South Africa ? *Journal of Yasar University*, *15*(58), 368–380.

Ikwor, O., & Nkama, N. (2018). Structural Breaks in Nigeria 's Macroeconomic Time Series Data. *Journal of Economics and Sustainable Development*, *9*(11), 49–56.

IMF. (2009). *Balance of Payments and International Investment Position manual*. Retrieved from http://www.imf.org/external/pubs/ft/bop/2007/pdf/bpm6.pdf

IMF. (2012). The Liberalization and Management of Capital Flows: An Institutional View. *Board Paper*.

IMF. (2013). *Ghana: 2013 Article IV Consultation; IMF Country Report*. Retrieved from https://www.imf.org/external/pubs/ft/scr/2013/cr13187.pdf

IMF. (2016a). Nigreria: 2016 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for Nigeria. *International Monetary Fund Staff Country Reports*, *16*(146), 1. https://doi.org/10.5089/9781513583624.002

IMF. (2016b). *Too Slow for Too Long: Understanding the Slowdown in Capital Flows to Emerging Markets*. *World Economic Outlook April 2016*. Retrieved from http://www.imf.org/external/pubs/ft/weo/2016/01/

IMF. (2016c). *World Economic Outlook, October 2016: Subdued Demand, Symptoms and Remedies*. *World Economic Outlook, October 2016*. https://doi.org/10.5089/9781513599540.081

IMF. (2020). Emerging and Frontier Markets Managing Volatile Portfolio Flows. *Global*

Financial Stability Report: Markets in the Time of COVID-19, (April), 47–66. Retrieved from https://www.imf.org/~/media/Files/Publications/GFSR/2020/April/English/ch3.ashx?la=en

Irungu, W. N., Chevallier, J., & Ndiritu, S. W. (2020). Regime Changes and Fiscal Sustainability in Kenya. *Economic Modelling*, *86*(January 2018), 1–9. https://doi.org/10.1016/j.econmod.2019.01.009

Johansen, B. S., & Niels, M. (2012). Likelihood Inference for a Fractionally Cointegrated Vector Autoregressive Model. *Econometrica*, *80*(6), 2667–2732. https://doi.org/10.3982/ecta9299

Jongwanich, J. (2019). Capital Controls in Emerging East Asia: How Do they Affect Investment Flows? *Journal of Asian Economics*, *62*(May 2018), 17–38. https://doi.org/10.1016/j.asieco.2019.04.001

Jouini, J., & Boutahar, M. (2005). Evidence on Structural Changes in U.S. Time Series. *Economic Modelling*, *22*(3), 391–422. https://doi.org/10.1016/j.econmod.2004.06.003

Kabashi, R., & Suleva, K. (2016). Loan Supply Shocks in Macedonia: A Bayesian SVAR Approach with Sign Restrictions. *Croatian Economic Survey*, *18*(1), 5–33. https://doi.org/10.15179/ces18.1.1

Kablan, S., & Kaabia, O. (2018). Transmission Channels of International Financial Crises to African Stock Markets: The Case of the Euro Sovereign Debt Crisis. *Applied Economics*, *50*(18), 1992–2011. https://doi.org/10.1080/00036846.2017.1383597

Kalemli-ozcan, S. (2020). Emerging Market Capital Flows under COVID : What to Expect Given What We Know. *IMF Research, Special Series on COVID-19*, (September), 1–5.

Kang, S. H., Mclver, R., Park, S.-Y., & Yoon, S.-M. (2014). Long Memory Features Evolve in the Time-Varying Process in Asia-Pacific Foreign Exchange Markets. *Procedia Economics and Finance*, *14*(14), 286–294. https://doi.org/10.1016/s2212-5671(14)00714-x

Kantelhardt, J. W. (2009). Fractal and Multifractal Time Series. *Encyclopedia of Complexity and Systems Sceince*, 3754–3779. https://doi.org/10.1007/978-1-4614-1806-1_30

Kass, R. E., & Wasserman, L. (1996). The Selection of Prior Distributions by Formal Rules. *Journal of the American Statistical Association*, *91*(435), 1343–1370. Retrieved from http://www.jstor.org/stable/2291752

Kemboi, J. K., & Tarus, D. K. (2012). Macroeconomic Determinants of Stock Market Development in Emerging Markets: Evidence from Kenya. *Research Journal of Finance and Accounting*, *3*(5), 57–69. https://doi.org/10.4103/ajm.AJM_124_16

Khan, U., Nallareddy, S., & Rouen, E. (2016). The Role of Taxes in the Disparity Between Corporate Performance and Economic Growth. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2712582

Khelifa, S., Kahlouche, S., & Belbachir, M. F. (2012). Signal and Noise Separation in Time Series of DORIS Station Coordinates Using Wavelet and Singular Spectrum Analysis. *Comptes Rendus - Geoscience*, *344*(6–7), 334–348.

https://doi.org/10.1016/j.crte.2012.05.003

Kilian, L., & Murphy, D. P. (2012). Why Agnostic Sign Restrictions are Not Enough: Understanding the Dynamics of Oil Market VAR Models. *Journal of the European Economic Association*, *10*(5), 1166–1188. https://doi.org/10.1111/j.1542-4774.2012.01080.x

Kim, S., & Lim, K. (2018). Effects of Monetary Policy Shocks on Exchange Rate in Small Open Economies. *Journal of Macroeconomics*, *56*(July 2017), 324–339. https://doi.org/10.1016/j.jmacro.2018.04.008

Kirabaeva, K., & Razin, A. (2010). Composition of Capital Flows: A Survey. *NBER Working Paper Series*, *16492*. https://doi.org/10.3386/w16492

Kirichenko, L., Radivilova, T., & Deineko, Z. (2011). Comparative Analysis for Estimating of the Hurst Exponent for Stationary and Nonstationary Time Series. *International Journal "Information Technologies & Knowledge*, *5*, 371–388.

Kitano, S. (2011). Capital Controls and Welfare. *Journal of Macroeconomics*, *33*(4), 700–710. https://doi.org/10.1016/j.jmacro.2011.07.004

Koepke, R. (2019). What Drives Capital Flows To Emerging Markets? A Survey of the Empirical Literature. *Journal of Economic Surveys*, *33*(2), 516–540. https://doi.org/10.1111/joes.12273

Kono, M., & Schuknecht, L. (1998). Financial Services Trade, Capital Flows, and Financial Stability. *World Trade Organization Staff Working Paper*, *ERAD-98-12*.

Koop, G., Poirier, D. J., & Tobias, J. L. (2007). *Bayesian econometric methods*. *Bayesian Econometric Methods*. https://doi.org/10.1017/CBO9780511802447

Korobilis, D. (2016). Prior Selection for Panel Vector Autoregressions. *Computational Statistics and Data Analysis*, *101*, 110–120. https://doi.org/10.1016/j.csda.2016.02.011

Kristoufek, L., & Vosvrda, M. (2013). Measuring Capital Market Efficiency: Global and Local Correlations Structure. *Physica A: Statistical Mechanics and Its Applications*, *392*(1), 184–193. https://doi.org/10.1016/j.physa.2012.08.003

Kuan, C. M., & Hornik, K. (1995). The Generalized Fluctuation Test: A Unifying View. *Econometric Reviews*. https://doi.org/10.1080/07474939508800311

Kumar, V. (2018). Dynamics of Private Capital Flows To India : a Structural Var Approach. *The Journal of Developing Areas*, *52*(4), 129–149.

Lafuerza, L. F., & Servén, L. (2019). *Swept by the Tide? The International Comovement of Capital Flows*. Washington DC.

Lahmiri, S. (2015). Long Memory in International Financial Markets Trends and Short Movements During 2008 Financial Crisis Based on Variational Mode Decomposition and Detrended Fluctuation Analysis. *Physica A: Statistical Mechanics and Its Applications*, *437*, 130–132.

Lai, T. (2010). *Capital Flows to China and the Issue of Hot Money: An Empirical Investigation*. Retrieved from https://www.rba.gov.au/publications/workshops/research/2010/pdf/lai.pdf

Lee, C., & Chou, P. (2020). Structural Breaks in the Correlations Between Asian and US

Stock Markets. *North American Journal of Economics and Finance*, *51*. https://doi.org/10.1016/j.najef.2019.101087

Leisch, F., Hornik, K., & Kuan, C.-M. (2000). Monitoring Structural Changes With the Generalized Fluctuation Test. *Econometric Theory*, *16*(6), 835–854. Retrieved from http://www.jstor.com/stable/3533257

Levchenko, A. A., & Mauro, P. (2007). Do Some Forms of Financial Flows Help Protect Against “Sudden Stops”? *World Bank Economic Review*, *21*(3), 389–411. https://doi.org/10.1093/wber/lhm014

Levine, R. (1997). Financial Development and Economic Growth: Views and Agenda. *Journal of Economic Literature*, *35*(2), 688–726. https://doi.org/10.1596/1813-9450-1678

Li, J., & Rajan, R. S. (2015). Do Capital Controls Make Gross Equity Flows to Emerging Markets Less Volatile? *Journal of International Money and Finance*, *59*, 220–244. https://doi.org/10.1016/j.jimonfin.2015.07.007

Li, M. (2013). On the Long-Range Dependence of Fractional Brownian Motion. *Mathematical Problems in Engineering*, *2013*(4), 1–5. https://doi.org/10.1155/2013/842197

Li, Ming, & Zhao, W. (2012). On 1 / f Noise. *Mathematical Problems in Engineering*, *2012*, 1–24. https://doi.org/10.1155/2012/673648

Li, Ming, Zhao, W., & Chen, S. (2010). FGN Based Telecommunication Traffic Models. *WSEAS Transactions on Computers*, *9*(7), 706–715.

Li, X., Su, C. W., Chang, H. L., & Ma, J. (2017). Do Short-Term International Capital Movements Play a Role in Exchange Rate and Stock Price Transmission Mechanism in China? *International Review of Economics and Finance*, 1–11. https://doi.org/10.1016/j.iref.2018.02.010

Li, Z., Chen, Y., Li, L., & Zhang, Y. (2009). Quantization Errors of Uniformly Quantized fGn and fBm Signals. *IEEE Signal Processing Letters*, *16*(12), 1059–1062. https://doi.org/10.1109/LSP.2009.2030115

Litterman, R. B. (1986). Forecasting with Bayesian Vector Autoregressions: Five Years of Experience. *Journal of Business & Economic Statistics*, *4*(1), 25–38.

Lo, A. W., & Mackinlay, A. C. (1988). Stock Market Prices do not Follow Random Walks : Evidence from a Simple Specification. *The Review of Financial Studies*, *1*(1), 41–66.

Lorenzo, E., & Miguel-Angel, G. (2000). International Capital Flows and Convergence in the Neoclassical Growth Model. *International Advances in Economic Research*, *6*(3), 451–460. https://doi.org/10.18356/ce953d4c-en

Løvsletten, O. (2017). Consistency of Detrended Fluctuation Analysis. *PHYSICAL REVIEW E96*, *012141*(July). https://doi.org/10.1103/PhysRevE.96.012141

Lu, X., Li, J., Zhou, Y., & Qian, Y. (2017). Cross-Correlations Between RMB Exchange Rate and International Commodity Markets. *Physica A: Statistical Mechanics and Its Applications*, *486*, 168–182. https://doi.org/10.1016/j.physa.2017.05.088

Lucas Jr, R. E. (1990). Why Doesn’t Capital Flow from Rich to Poor Countries? *American Economic Review*, *Volume 80*(2), 92–96.

Magud, N. E., Reinhart, C. M., & Rogoff, K. S. (2018). Capital Controls: Myth and Reality. *Annals of Economics and Finance*, *19*(1), 1–47.

Mahadevan, R., & Asafu-Adjaye, J. (2007). Energy Consumption, Economic Growth and Prices: A Reassessment Using Panel VECM for Developed and Developing Countries. *Energy Policy*, *35*(4), 2481–2490. https://doi.org/10.1016/j.enpol.2006.08.019

Makarava, N. (2012). *Bayesian Estimation of Self-Similarity Exponent. PhD Thesis, University of Potsdam*.

Mandelbrot, B. & Van, N. J. (1968). Fractional Brownian Motions , Fractional Noises and Applications. *SIAM Review*, *10*(4), 422–437. https://doi.org/10.1137/1010093

Maria, G., & Luis, A. (2020). *Inflation in the G7 Countries : Persistence and Structural*. *CESifo Working Paper, No. 8349, Center for Economic Studies and Ifo Institute (CESifo), Munich*. Munich.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance, 7*(1), 77–91.

Marmelat, V., Torre, K., & Delignières, D. (2012). Relative Roughness: An Index for Testing the Suitability of the Monofractal Model. *Frontiers in Physiology*, *3 JUN*(June), 1–11. https://doi.org/10.3389/fphys.2012.00208

Marques, C. R. (2005). Inflation Persistence: Facts or Artefacts?*. *Banco de Portugal Economic Bulletin*, (Summer 2005), 69–79. Retrieved from https://www.bportugal.pt/sites/default/files/anexos/papers/ab200508_e.pdf

Martinez, L. B., Guercio, M. B., Bariviera, A. F., & Terceño, A. (2016). The Impact of the Financial Crisis on the Long-Range Memory of European Corporate Bond and Stock Markets. *Empirica*, 1–15. https://doi.org/10.1007/s10663-016-9340-8

Massa, I., & Macias, J. B. (2009). The Global Financial Crisis and Sub- Saharan Africa: The Effects of Slowing Private Capital Inflows on Growth. *Overseas Development Institute Working Papers*, *Working Pa*.

McQuade, P., & Schmitz, M. (2017). The Great Moderation in International Capital Flows: A Global Phenomenon? *Journal of International Money and Finance*, *73*, 188–212. https://doi.org/10.1016/j.jimonfin.2017.02.027

Mensi, W., Tiwari, A. K., & Al-Yahyaee, K. H. (2019). An Analysis of the Weak Form Efficiency, Multifractality and Long Memory of Global, Regional and European Stock Markets. *Quarterly Review of Economics and Finance*, *72*, 168–177. https://doi.org/10.1016/j.qref.2018.12.001

Mercado, R. V. (2019). Capital flow Transitions: Domestic Factors and Episodes of Gross Capital Inflows. *Emerging Markets Review*, *38*(October 2018), 251–264. https://doi.org/10.1016/j.ememar.2019.02.002

Mercado, R. V. (2020). Are Capital Inflows Expansionary or Contractionary in the Philippines? *Journal of Asian Economics*, (Available online 30 January 2020, 101176). Retrieved from https://www.sciencedirect.com/science/article/pii/S1049007820300208

Mlambo, C., Maredza, A., & Sibanda, K. (2013). Effects of Exchange Rate Volatility on the Stock Market: A Case Study of South Africa. *Mediterranean Journal of Social Sciences*, *4*(14), 561–570. https://doi.org/10.5901/mjss.2013.v4n14p561

Monfort, P. (2008). Convergence of EU Regions Measures and Evolution. *European Union - Regioanl Policy*, No. 01/2008.

Montanari, A., Taqqu, M. S., & Teverovsky, V. (1999). Estimating Long-Range Dependence in the Presence of Periodicity: An Empirical Study. *Mathematical and Computer Modelling*, *29*(10–12), 217–228. https://doi.org/10.1016/S0895-7177(99)00104-1

Montiel, P., & Reinhart, C. M. (1999). Do Capital Controls and Macroeconomic Policies Influence the Volume and Composition of Capital Flows ? Evidence from the 1990s. *Journal of International Money and Finance*, *18*, 619–635.

Moon, H. R., & Schorfheide, F. (2012). Bayesian and Frequentist Inference in Partially Identified Models. *Econometrica*, *80*(2), 755–782.

Mordi, N. O. (2006). Challenges of Exchange Rate Volatility in Economic Management in Nigeria. In The Dynamics of Exchange Rate in Nigeria. *Central Bank of Nigeria Bullion*, *30*(3), 17–25.

Moss, B. T., Ramachandran, V., & Standley, S. (2007). Why Doesn ' t Africa Get More Equity Investment ? Fronteir Stock Markets, Firm Size and Asset Allocations of Global Emerging Market Funds. *Center for Global Development*, *WP*(112).

Mukherjee, P., Bose, S., & Coondoo, D. (2002). FII in the Indian Equity Market: An Analysis of Daily Flows during January. *Money and Finance*, (May), 21–51.

Mulligan, R. F. (2004). Fractal analysis of highly volatile markets: An application to technology equities. *Quarterly Review of Economics and Finance*, *44*(1), 155–179. https://doi.org/10.1016/S1062-9769(03)00028-0

Mulligan, R. F., & Koppl, R. (2011). Monetary Policy Regimes in Macroeconomic Data : An Application of Fractal Analysis. *Quarterly Review of Economics and Finance*, *51*(2), 201–211. https://doi.org/10.1016/j.qref.2011.01.001

Mumtaz, H., Arze del Granado, F. J., Jang, B. K., & Corrales, J.-S. (2014). *Managing Volatile Capital Flows: Experiences and Lessons for Sub-Saharan African Frontier Markets*. Washintone DC: International Monetary Fund. Retrieved from www.elibrary.imf.org

Musongole, C. M. C. (2002). *Fuzzy Modelling of the Joannesburg Security Exchange Overall Index*. University of Cape Town.

Muthuramu, P., & Uma Maheswari, T. (2019). Tests for Structural Breaks in Time Series Analysis: A Review of Recent Development. *Shanlax International Journal of Economics*, *7*(4), 66–79. https://doi.org/10.34293/economics.v7i4.628

Nagy, Z., Mukli, P., Herman, P., & Eke, A. (2017). Decomposing Multifractal Crossovers. *Frontiers in Physiology*, *8*(JUL). https://doi.org/10.3389/fphys.2017.00533

Ndong, B. (2015). Effect of Portfolio Equity Investment Flows on Equity Returns and Economic Growth in 11 Major African Stock Markets. *International Journal of Economics and Finance*, *7*(2), 225–240. https://doi.org/10.5539/ijef.v7n2p225

Neanidis, K. C. (2019). Volatile Capital Flows and Economic Growth: The Role of Banking Supervision. *Journal of Financial Stability*, *40*, 77–93. https://doi.org/10.1016/j.jfs.2018.05.002

Neumann, R. M., Penl, R., & Tanku, A. (2009). Volatility of Capital Flows and Financial

Liberalization: Do Specific Flows Respond Differently? *International Review of Economics and Finance*, *18*(3), 488–501. https://doi.org/10.1016/j.iref.2008.04.005

Neyman, J., & Pearson, E. S. (1933). On the Problem of the Most Efficient Tests of Statistical Hypotheses. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*. https://doi.org/10.1098/rsta.1933.0009

Ng, A., Ibrahim, M. H., & Mirakhor, A. (2016). Does Trust Contribute to Stock Market Development ? *Economic Modelling*, *52*, 239–250. https://doi.org/10.1016/j.econmod.2014.10.056

Ngene, G., Tah, K. A., & Darrat, A. F. (2017). Review of Financial Economics Long Memory or Structural Breaks : Some Evidence for African Stock Markets. *Review of Financial Economics*, *34*, 61–73. https://doi.org/10.1016/j.rfe.2017.06.003

Nguyen, A. D. M., Dridi, J., Unsal, F. D., & Williams, O. H. (2017). On the Drivers of Inflation in Sub-Saharan Africa. *International Economics*, *151*, 71–84. https://doi.org/10.1016/j.inteco.2017.04.002

Nguyen, D. B. B., Prokopczuk, M., & Sibbertsen, P. (2019). The Memory of Stock Return Volatility: Asset Pricing Implications. *Journal of Financial Markets*, *Available*. https://doi.org/10.2139/ssrn.3074550

Ning, Y., Wang, Y., Yang, Z., & Geng, Y. (2017). Measurement and Multifractal Properties of Short-Term International Capital Flows in China. *Physica A: Statistical Mechanics and Its Applications*, *468*, 714–721. https://doi.org/10.1016/j.physa.2016.10.063

Nkoro, E., & Uko, K. A. (2016). Autoregressive Distributed Lag (ARDL) Cointegration Technique: Application and Interpretation. *Journal of Statistical and Econometric Methods*, *5*(3), 63–91.

Nyaga, K. L. (2017). *Effects of Foreign Portfolio Flows on the Capital Market in Kenya*. University of Nairobi.

Nyblom, J. (1989). Testing for the Constancy of Parameters Over Time. *Journal of the American Statistical Association*, *84*(405), 223–230. https://doi.org/10.1080/01621459.1989.10478759

O'Hagan, A., Buck, C. E., Daneshkhah, A., Eiser, J. R., Garthwaite, P. H., Jenkinson, D. J., … Rakow, T. (2006). *Uncertain judgements: Eliciting experts' probabilities*. *Uncertain Judgements: Eliciting Experts' Probabilities*. https://doi.org/10.1002/0470033312

Obayelu, A. E., & Salau, A. S. (2010). Agricultural Response to Prices and Exchange Rate in Nigeria: Application of Co-integration and Vector Error Correction Model (VECM). *Journal of Agricultural Sciences*, *1*(2), 73–81. https://doi.org/10.1080/09766898.2010.11884656

Obstfeld, M., & Rogoff, K. (2001). The Six Major Puzzles in International Macroeconomics: Is There a Common Cause? *NBER Macroeconomics Annual 2000*, *15*, 339–412.

OECD/United Nations. (2011). *Economic Diversification in Africa: A Review of Selected Countries*. *OECD Publishing*. Retrieved from http://dx.doi.org/10.1787/9789264038059-en

Olufemi, A. P., Adewale, A. O., & Oseko, M. S. (2017). Efficiency of Foreign Exchange Markets in Sub-Saharan Africa in the Presence of Structural Break: A Linear and Non-Linear Testing Approach. *Journal of Economics and Behavioral Studies*, *9*(4), 122–131.

Olugbenga, A. A. (2012). Exchange Rate Volatility and Stock Market Behaviour : The Nigerian Experience. *European Journal of Business and Management*, *4*(5), 31–40.

Onali, E., & Goddard, J. (2011). Are European equity markets efficient? New evidence from fractal analysis. *International Review of Financial Analysis*, *20*(2), 59–67. https://doi.org/10.1016/j.irfa.2011.02.004

Opperman, P., Delali, A., & Komla, C. (2017). The Determinants of Private Capital Flow Volatility in Sub-Saharan African Countries. *Research in International Business and Finance*, *42*(November 2015), 312–320. https://doi.org/10.1016/j.ribaf.2017.07.146

Osaseri, G., & Osamwonyi, I. O. (2019). Impact of Stock Market Development on Economic Growth in BRICS. *International Journal of Financial Research*, *10*(1), 23. https://doi.org/10.5430/ijfr.v10n1p23

Ostry, J. D., Ghosh, A. R., Chamon, M., & Mahvash, S. (2011). Capital Controls : When and Why ? *IMF Economic Review*, *59*(3), 562–580.

Ouedraogo, R., & Sandrine, W. (2018). Fiscal Policy Pro-Cyclicality in Sub-Saharan African Countries : The Role of Export Concentration. *Economic Modelling*, *74*(May), 219–229. https://doi.org/10.1016/j.econmod.2018.05.017

Pamu, E. M., Musongole, M. C., & Chokwe, E. (2012). The Kwacha - US Dollar Exchange Rate: Is it a Random Walk? *Issues on the Zambian Economy: BoZ Reader*, *01*(08), 19–27.

Pan, L., & Mishra, V. (2018). Stock Market Development and Economic Growth: Empirical Evidence from China. *Economic Modelling*, *68*(April 2017), 661–673. https://doi.org/10.1016/j.econmod.2017.07.005

Papaioannou, G. P., Dikaiakos, C., Stratigakos, A. C., Papageorgiou, P. C., & Krommydas, K. F. (2019). Testing the Efficiency of Electricity Markets Using a New Composite Measure Based on Nonlinear TS Tools. *Energies*, *12*(4). https://doi.org/10.3390/en12040618

Pasricha, G. K. (2017). Policy Rules for Capital Controls. *BIS Working Papers*, *670*. https://doi.org/10.2139/ssrn.3040092

Pasricha, G. K., Falagiarda, M., Bijsterbosch, M., & Aizenman, J. (2018a). Domestic and Multilateral Effects of Capital Controls in Emerging Markets. *Journal of International Economics*, *115*, 48–58. https://doi.org/10.1016/j.jinteco.2018.08.005

Pasricha, G. K., Falagiarda, M., Bijsterbosch, M., & Aizenman, J. (2018b). Domestic and Multilateral Effects of Capital Controls in Emerging Markets. *Journal of International Economics*, *115*, 48–58. https://doi.org/10.1016/j.jinteco.2018.08.005

Peersman, G. (2005). What Caused the Early Millennium Slowdown? Evidence Based on Vector Autoregressions. *Journal of Applied Econometrics*, *20*(2), 185–207.

https://doi.org/10.1002/jae.832

Peng, C. K., Buldyrev, S. V., Havlin, S., Simons, M., Stanley, H. E., & Goldberger, A. L. (1994). Mosaic organization of DNA nucleotides. *Physical Review E*, *49*(2), 1685–1689. https://doi.org/10.1103/PhysRevE.49.1685

Peranginangin, Y., Ali, A. Z., Brockman, P., & Zurbruegg, R. (2016). The Impact of Foreign Trades on Emerging Market Liquidity. *Pacific Basin Finance Journal*, *40*, 1–16. https://doi.org/10.1016/j.pacfin.2016.07.002

Pesenti, P., & van Wincoop, E. (1996). Do Non Traded Goods Explain the Home Bias Puzzle? *NBER Working Paper 5784*.

Peters, E. E. (1991). Chaos and Order in the Capital Markets. A New View of Cycle, Prices, and Market Volatility. *J. WILEY*. https://doi.org/10.2307/2329084

Phinyomark, A., Larracy, R., & Scheme, E. (2020). Fractal Analysis of Human Gait Variability via Stride Interval Time Series. *Frontiers in Physiology*, *11*(April), 1–12. https://doi.org/10.3389/fphys.2020.00333

Pilgram, B., & Kaplan, D. T. (1998). A Comparison of Estimators for 1/f Noise. *Physica D: Nonlinear Phenomena*, *114*(1–2), 108–122. https://doi.org/10.1016/S0167-2789(97)00188-7

Polbin, A., Skrobotov, A., & Zubarev, A. (2019). How the Oil Price and other Factors of Real Exchange Rate Dynamics Affect Real GDP in Russia. *Emerging Markets Finance and Trade*. https://doi.org/10.1080/1540496X.2019.1573667

Portes, R., & Rey, H. (2005). The Determinants of Cross-Border Equity Flows. *Journal of International Economics*, *65*, 269–296. Retrieved from http://www.sciencedirect.com.ezproxy.uct.ac.za/science/article/pii/S0022199604000716

Pradhan, M., Balakrishnan, R., Baqir, R., Heenan, G., Nowak, S., Oner, C., & Panth, S. (2011). Policy Responses to Capital Flows in Emerging Markets. *IMF Staff Discussion Note*, (SDN/11/10).

Pradhan, R. P., & Bagchi, T. P. (2013). Effect of Transportation Infrastructure on Economic Growth in India: The VECM Approach. *Research in Transportation Economics*, *38*(1), 139–148. https://doi.org/10.1016/j.retrec.2012.05.008

Preuss, P., Puchstein, R., Dette, H., Reuss, P. P., Uchstein, R. P., & Ette, H. D. (2015). Detection of Multiple Structural Breaks in Multivariate Time Series. *Journal of the American Statistical Association*, *110*(510), 654–668. https://doi.org/10.1080/01621459.2014.920613

Quandt, R. E. (1958). The Estimation of the Parameters of a Linear Regression System Obeying Two Separate Regimes. *Journal of the American Statistical Association*, *53*(284), 873–880.

Rapach, D. E., Wohar, M. E., & Wohar, M. E. (2005). Regime Changes in International Real Interest Rates : Are They a Monetary Phenomenon ? *Journal of Money, Credit and Banking*, *37*(5), 887–906. Retrieved from https://about.jstor.org/

Rea, W., Oxley, L., Reale, M., & Brown, J. (2013). Not All Estimators are Born Equal: The Empirical Properties of Some Estimators of Long Memory. *Mathematics and Computers in Simulation*, *93*, 29–42.

https://doi.org/10.1016/j.matcom.2012.08.005

Resta, M. (2012). Hurst Exponent and its Applications in Time-Series Analysis. *Recent Patents on Computer Science*, *5*(3), 211–219.

Robert, L. W. (1967). The Assessment of Prior Distributions in Bayesian Analysis. *Journal of the American Statistical Association*, *62*(319), 776–800.

Robinson, P. M., & Velasco, C. (2015). Efficient Inference on Fractionally Integrated Panel Data Models with Fixed Effects. *Journal of Econometrics*, *185*(2), 435–452. https://doi.org/10.1016/j.jeconom.2014.12.003

Robinson, P. M., & Velasco, C. (2018). Inference on Trending Panel Data. *Journal of Econometrics*, *206*(2), 282–304. https://doi.org/10.1016/j.jeconom.2018.06.003

Robstad, Ø. (2018). House Prices, Credit and the Effect of Monetary Policy in Norway: Evidence from Structural VAR Models. *Empirical Economics*, *54*(2), 461–483. https://doi.org/10.1007/s00181-016-1222-1

Roch, F. (2019). The Adjustment to Commodity Price Shocks. *Journal of Applied Economics*, *22*(1), 437–467. https://doi.org/10.1080/15140326.2019.1665316

Rule, G. (2015). *Centre for Central Banking Studies: Understanding the central bank balance sheet*. *Bank of England*.

Sá, F., Towbin, P., & Wieladek, T. (2014). Capital Inflows, Financial Structure and Housing Booms. *Journal of the European Economic Association*, *12*(2), 522–546. https://doi.org/10.1111/jeea.12047

Sá, F., & Wieladek, T. (2015). Capital Inflows and the US Housing Boom. *Journal of Money, Credit and Banking*, *47*(51), 221–256. Retrieved from https://onlinelibrary.wiley.com/doi/full/10.1111/jmcb.12200

Sachs, J., Tornell, A., & Velasco, A. (1996). Financial Crises in Emerging Markets: The Lessons from 1995. *NBER Working Paper Series*, (5576).

Sahay, R., Arora, V., Arvanitis, T., & Faruqee, H. (2014). Emerging Market Volatility: Lessons from The Taper Tantrum. *IMF Staff Discussion Note*, (SDN/14/09). Retrieved from https://www.imf.org/external/pubs/ft/sdn/2014/sdn1409.pdf

Salacuse, J. W. (2017). Of Handcuffs and Signals: Investment Treaties and Capital Flows to Developing Countries. *Harvard International Law Journal*, *58*(1), 127–176. https://doi.org/10.3366/ajicl.2011.0005

Salisu, A. A., Ndako, U. B., Adediran, I. A., & Swaray, R. (2019). A Fractional Cointegration VAR Analysis of Islamic Stocks : A Global Perspective. *North American Journal of Economics and Finance*, (December 2018), 101056. https://doi.org/10.1016/j.najef.2019.101056

SARB. (2006a). Quarterly Economic Review. *Quarterly Bulletin, South African Reserve Bank*, *240*(June), 1–52. Retrieved from https://www.resbank.co.za/Lists/News and Publications/Attachments/4356/Quarterly Economic Review.pdf

SARB. (2006b). Quarterly Economic Review. *Quarterly Bulletin, South African Reserve Bank*, *239*(March), 1–63. Retrieved from https://www.resbank.co.za/Lists/News and Publications/Attachments/4361/Quarterly Economic Review.pdf

Sarno, L., & Taylor, M. P. (1999a). Hot Money, Accounting Labels and the Permanence of

Capital Flows to Developing Countries: An Empirical Investigation. *Journal of Development Economics*, *59*(2), 337–364. https://doi.org/10.1016/S0304-3878(99)00016-4

Sarno, L., & Taylor, M. P. (1999b). Moral Hazard , Asset Price Bubbles , Capital Flows , and the East Asian crisis : The First Tests. *Journal of International Money and Finance*, *18*, 637–657.

Sarno, L., Tsiakas, I., & Ulloa, B. (2016). What Drives International Portfolio Flows? *Journal of International Money and Finance*, *60*, 53–72. https://doi.org/10.1016/j.jimonfin.2015.03.006

Schaefer, A., Brach, J. S., Perera, S., & Sejdić, E. (2014). A Comparative Analysis of Spectral Exponent Estimation Techniques for 1/f^β Processes With Applications to the Analysis of Stride Interval Time Series. *Journal of Neuroscience Methods*, *222*, 118–130. https://doi.org/10.1016/j.jneumeth.2013.10.017

Schasfoort, J. (2017). Complexity Economics. *Exploring Economics*, (downloaded on 8 August 2019). Retrieved from https://www.exploring-economics.org/en/

Schuppli, M., & Bohl, M. T. (2010). Do Foreign Institutional Investors Destabilize China's A-Share Markets? *Journal of International Financial Markets, Institutions and Money*, *20*(1), 36–50. https://doi.org/10.1016/j.intfin.2009.10.004

Sengupta, R., & Sen Gupta, A. (2019). Alternate Instruments to Manage the Capital Flow Conundrum: A Study of Selected Asian Economies. *Pacific Economic Review*, *24*(2), 241–268. https://doi.org/10.1111/1468-0106.12296

Sensoy, A. (2013). Generalized Hurst Exponent Approach to Efficiency in MENA Markets. *Physica A: Statistical Mechanics and Its Applications*, *392*(20), 5019–5026. https://doi.org/10.1016/j.physa.2013.06.041

Sensoy, Ahmet, & Tabak, B. M. (2015). Time-Varying Long Term Memory in the European Union Stock Markets. *Physica A: Statistical Mechanics and Its Applications*, *436*, 147–158. https://doi.org/10.1016/j.physa.2015.05.034

Sensoy, Ahmet, & Tabak, B. M. (2016). Dynamic Efficiency of Stock Markets and Exchange Rates. *International Review of Financial Analysis*, *47*, 353–371. https://doi.org/10.1016/j.irfa.2016.06.001

Serinaldi, F. (2010). Use and Misuse of Some Hurst Parameter Estimators Applied to Stationary and Non-Stationary Financial Time Series. *Physica A: Statistical Mechanics and Its Applications*, *389*(14), 2770–2781. https://doi.org/10.1016/j.physa.2010.02.044

Sezgin, F., & Atakan, T. (2015). The Role of the Calderon-Rossell Model on Determining the Developments of Equity Capital Markets: A Study of Fragile Five Countries. *Istanbul University Journal of the School of Business Administration*, *44*(1), 2–11. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=111650961&site=ehost-live&scope=site

Shakhawat Hossain, M., & Rokonuzzaman, M. (2018). Impact of Stock Market, Trade, and Bank on Economic Growth for Latin American Countries: An Econometrics Approach. *Science Journal of Applied Mathematics and Statistics*, *6*(1), 1. https://doi.org/10.11648/j.sjams.20180601.11

Shevchenko, G. (2015). Fractional Brownian Motion in a Nutshell. *International Journal of Modern Physics: Conference Series*, *36*(2014), 1560002. https://doi.org/10.1142/S2010194515600022

Shu, C., He, D., Dong, J., & Wang, H. (2018). Regional pull vs global push factors: China and US influence on Asian financial markets. *Journal of International Money and Finance*, *87*, 112–132. https://doi.org/10.1016/j.jimonfin.2018.04.004

Simonsen, I., Hansen, A., & Nes, O. M. (1998). Determination of the Hurst Exponent by Use of Wavelet Transforms. *Physical Review E*, *58*(3), 2779–2787. https://doi.org/10.1103/PhysRevE.58.2779

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, *48*(1), 1–48. https://doi.org/10.2307/2223855

Sims, C. A. (1993). *A 9 Variable Probabilistic Macroeconomic Forecasting Model*. *Business Cycles, Indicators, and Forecasting* (Vol. 28). Retrieved from http://www.nber.org/chapters/c7192.pdf

Sims, C. A., & Uhlig, H. (1991). Understanding Unit Rooters : A Helicopter Tour. *Econometrica*, *59*(6), 1591–1599.

Sims, C. A., & Zha, T. (1995). Error Bands for Impulse Responses. *Working Paper No. 95-6, Federal Reserve Bank of Atlanta, Atlanta, GA*.

Sims, C. A., & Zha, T. (1999). Error Bands for Impulse Responses. *Econometrica*, *67*(5), 1113–1155. https://doi.org/10.1111/1468-0262.00071

Singhania, M., & Saini, N. (2018). Determinants of FPI in Developed and Developing Countries. *Global Business Review*, *19*(1), 187–213. https://doi.org/10.1177/0972150917713280

Škare, M., & Stjepanović, S. (2013). A Fractionally Integrated Model for the Croatian Aggregate Output (GDP) Series. *Frakcionirano Integrirani Model Za Niz Hrvatskog Ukupnog Outputa (BDP)*, *26*(2), 1–34. Retrieved from http://www.scopus.com/inward/record.url?eid=2-s2.0-84879321749&partnerID=40&md5=aa37b7816ae41115bfc7ff8b3bb9db30

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, *70*(1), 65–94. Retrieved from http://www.jstor.org/stable/1884513

Stadnitski, T. (2012). Measuring Fractality. *Frontiers in Physiology*, *3 MAY*(May), 1–13. https://doi.org/10.3389/fphys.2012.00127

Stiglitz, J. E. (2008). Capital Market Liberalization, Globalization, and the IMF. In J. A. Ocampo & J. E. Stiglitz (Eds.), *Capital Market Liberalization and Development* (2008th ed.). New York: Oxford University Press.

Sukcharoensin, P., & Sukcharoensin, S. (2013). The Analysis of Stock Market Development Indicators: Evidence from the ASEAN-5 Equity Markets. *International Journal of Trade, Economics and Finance*, *4*(6), 343–346. https://doi.org/10.7763/ijtef.2013.v4.314

Swanepoel, J., & Schoeman, N. (2003). Countercyclical Fiscal Policy in South Africa: Role and Impact of Automatic Fiscal Stabilisers. *South African Journal of Economic and Management Sciences*, *6*(4), 802–822. https://doi.org/10.4102/sajems.v6i4.1523

Taleb, Nassim, N. (2019). *The Statistical Consequences of Fat Tails (Technical Incerto Collection)*. STEM Academic Press. Retrieved from https://www.academia.edu/37221402/STATISTICAL_CONSEQUENCES_OF_FAT_TAILS_TECHNICAL_INCERTO_COLLECTION_

Tamási, B., & Világi, B. (2011). Identification of Credit Supply Shocks in a Bayesian SVAR Model of the Hungarian Economy. *MNB Working Papers*, *7*, 1–21.

Taqqu, M. S., Teverovsky, V., & Willinger, W. (1995). Estimators for Long-Range Dependence: An Empirical Study. *Fractals*, *3*(4), 785–798.

Tarasov, V. E., & Tarasova, V. V. (2016). Long and Short Memory in Economics: Fractional-Order Difference and Differentiation. *IRA-International Journal of Management & Social Sciences (ISSN 2455-2267)*, *5*(2), 327. https://doi.org/10.21013/jmss.v5.n2.p10

Tarasov, V. E., & Tarasova, V. V. (2018). Criterion of Existence of Power-Law Memory for Economic Processes. *Entropy*, *20*(6), 1–24. https://doi.org/10.3390/e20060414

Tarasova, V. V., & Tarasov, V. E. (2018). Concept of Dynamic Memory in Economics. *Communications in Nonlinear Science and Numerical Simulation*, *55*, 127–145. https://doi.org/10.1016/j.cnsns.2017.06.032

Taylor, M. P., & Sarno, L. (1997). Capital Flows to Developing Countries: Long- and Short-Term Determinants. *World Bank Economic Review*, *11*(3), 451–470. https://doi.org/10.1093/wber/11.3.451

Tetsuya, K., & Villafuerte, M. (2016). *Cyclical Behavior of Fiscal Policy among Sub-Saharan African Countries*. Washington DC. Retrieved from https://www.imf.org/external/pubs/ft/dp/2016/afr1604.pdf

Tevdovski, D., Petrevski, G., & Bogoev, J. (2019). The Effects of Macroeconomic Policies Under Fixed Exchange Rates: A Bayesian VAR Analysis. *Economic Research-Ekonomska Istrazivanja*, *32*(1), 2138–2160. https://doi.org/10.1080/1331677X.2019.1579661

Tillmann, P. (2013). Capital Inflows and Asset Prices : Evidence from Emerging Asia. *Journal of Banking and Finance*, *37*(3), 717–729. https://doi.org/10.1016/j.jbankfin.2012.10.017

Torre, K., Delignières, D., & Lemoine, L. (2007). 1/f β Fluctuations in Bimanual Coordination: An Additional Challenge for Modeling. *Experimental Brain Research*, *183*(2), 225–234. https://doi.org/10.1007/s00221-007-1035-8

Uhlig, H. (2005). What Are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure. *Journal of Monetary Economics*, *52*(2), 381–419. https://doi.org/10.1016/j.jmoneco.2004.05.007

Ülkü, N., & Ikizlerli, D. (2012). The Interaction Between Foreigners' Trading and Emerging Stock Returns: Evidence from Turkey. *Emerging Markets Review*, *13*(3), 381–409. https://doi.org/10.1016/j.ememar.2012.06.002

van de Schoot, R., & Depaoli, S. (2014). Bayesian Analyses: Where to Start and What to Report. *The Europan Helath Psychologist*, *16*(2), 75–84. Retrieved from http://www.ehps.net/ehp/issues/2014/v16iss2April2014/16_2_EHP_April 2014.pdf#page=41

Velasquez, T. (2010). Chaos Theory and the Science of Fractals in Finance. *Odeon*, (5), 229–264. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1866332

Vithessonthi, C., & Tongurai, J. (2012). The Impact of Capital Account Liberalization Measures. *Journal of International Financial Markets, Institutions and Money*, *22*(1), 16–34. https://doi.org/10.1016/j.intfin.2011.07.003

Vo, X. V. (2018). Determinants of Capital Flows to Emerging Economies - Evidence from Vietnam. *Finance Research Letters*, *27*, 23–27. https://doi.org/10.1016/j.frl.2018.02.031

Wah Hlaing, S., & Kakinaka, M. (2019). Global Uncertainty and Capital Flows: Any Difference Between Foreign Direct Investment and Portfolio Investment? *Applied Economics Letters*, *26*(3), 202–209. https://doi.org/10.1080/13504851.2018.1458182

Wang, C., Hwang, J., & Chung, C. (2016). Do Short-Term International Capital Inflows Drive China ' s Asset Markets ? *Quarterly Review of Economics and Finance*, *60*, 115–124. https://doi.org/10.1016/j.qref.2015.10.006

Wang, M., & Maruyama, Y. (2016). Consistency of Bayes Factor for Nonnested Model Selection When the Model Dimension Grows. *Bernoulli*, *22*(4), 2080–2100. https://doi.org/10.3150/15-BEJ720

Wei, Y., Yu, Q., Liu, J., & Cao, Y. (2018). Hot Money and China's Stock Market Volatility: Further Evidence Using the GARCH–MIDAS Model. *Physica A: Statistical Mechanics and Its Applications*, *492*, 923–930. https://doi.org/10.1016/j.physa.2017.11.022

Wenger, K., Leschinski, C., & Sibbertsen, P. (2018). A Simple Test on Structural Change in Long-Memory Time Series. *Economics Letters*, *163*, 90–94. https://doi.org/10.1016/j.econlet.2017.12.007

Yang, H., Shi, F., Wang, J., & Jing, Z. (2019). Investigating the Relationship Between Financial Liberalization and Capital Flow Waves: A Panel Data Analysis. *International Review of Economics and Finance*, *59*, 120–136. https://doi.org/10.1016/j.iref.2018.08.011

Yao, Y.-C., & Au, S. T. (1989). Least-Squares Estimation of a Step Function. *Sankhyā: The Indian Journal of Statistics, Series A*, *51*(3), 370–381. Retrieved from http://www.jstor.org/stable/25050759

Yartey, C A, & Adjasi, C. K. (2007). Stock Market Development in Sub-Saharan Africa : Critical Issues and Challenges. *IMF - Working Paper*, (07/209), 1–33. https://doi.org/10.5089/9781451867732.001

Yartey, Charles Amo. (2008). The Determinants of Stock Market Development in Emerging Economies: Is South Africa Different? *IMF Working Paper, WP08/32*, 1–31. https://doi.org/10.5089/9781451868944.001

Yartey, Charles Amo. (2010). The Institutional and Macroeconomic Determinants of Stock Market Development in Emerging Economies. *Applied Financial Economics*, *20*(21), 1615–1625. https://doi.org/10.1080/09603107.2010.522519

Yin, L., & Ma, X. (2020). Oil Shocks and Stock Volatility: New Evidence Via a Bayesian, Graph-Based VAR Approach. *Applied Economics*, *52*(11), 1163–1180.

https://doi.org/10.1080/00036846.2019.1659497

Yin, Y. Q. (1988). Detection of the Number, Locations and Magnitudes of Jumps. *Communications in Statistics. Stochastic Models*. https://doi.org/10.1080/15326348808807089

Ying, L., Feng-ju, Z., Kang, L., & Xiang-yang, L. (2011). Study of Wireless Network Traffic Model and Design of Traffic Generation Method Based on OPNET In: Zheng D. (eds) Advances in Electrical Engineering and Electrical Machines. *Lecture Notes in Electrical Engineering*, *134*, 667–674. Retrieved from https://doi.org/10.1007/978-3-642-25905-0_86

Zaremba, A., & Maydybura, A. (2019). The Cross-Section of Returns in Frontier Equity Markets: Integrated or Segmented Pricing? *Emerging Markets Review*, *38*(December 2018), 219–238. https://doi.org/10.1016/j.ememar.2019.02.003

Zeileis, A. (2005). A Unified Approach to Structural Change Tests Based on ML Scores, F Statistics, and OLS Residuals. *Econometric Reviews*, *24*(4), 445–466. https://doi.org/10.1080/07474930500406053

Zeileis, A., Kleiber, C., Walter, K., & Hornik, K. (2003). Testing and Dating of Structural Changes in Practice. *Computational Statistics and Data Analysis*, *44*(1–2), 109–123. https://doi.org/10.1016/S0167-9473(03)00030-6

Zeileis, A., Leisch, F., Hornik, K., & Kleiber, C. (2002). Strucchange: An R Package for Testing for Structural Change in Linear Regression Models. *Journal of Statistical Software*, *7*, 1–38. https://doi.org/10.18637/jss.v007.i02

Zhang, L., & Zoli, E. (2016). Leaning Against the Wind: Macroprudential Policy in Asia. *Journal of Asian Economics*, *42*, 33–52. https://doi.org/10.1016/j.asieco.2015.11.001

Zheng, M., Liu, R., & Li, Y. (2018). Long Memory in Financial Markets: A Heterogeneous Agent Model Perspective. *International Review of Financial Analysis*, *58*(March), 38–51. https://doi.org/10.1016/j.irfa.2018.04.001

Appendices

Related to Chapter 3:

A3.1. R Codes for Structural Break Identification

```
#Structural Break Testing for Data on Portfolio flows PhD Project
#By Francis Ziwele Mbao-MBXFRA001
#University of Cape Town
#Department of Finance and Tax

## House Keeping measures: clear data & close graphs
rm(list=ls())
graphics.off()

## change directory
setwd("~/Documents/Thesis Empirics_Mac/Empirical_data")

library('strucchange')

##############################################################
                      #(A) South African Data
#############################################################

#(1) load South Africa FPEI data and create time series object
dat <- read.csv(file="FPEI_SA.csv", sep=",")
FPEI_SA <- ts(dat$FPEI_SA, start=c(1994,1), frequency=12)

#Structural Break Identification
bp.FPEI_SA<- breakpoints(FPEI_SA ~ 1)
summary(bp.FPEI_SA)
plot(bp.FPEI_SA)

## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.FPEI_SA)

## confidence intervals
ci.FPEI_SA <- confint(bp.FPEI_SA)
breakdates(ci.FPEI_SA)
ci.FPEI_SA
plot(FPEI_SA)
lines(ci.FPEI_SA)

#(2) load South Africa FPEO data and create time series object
dat <- read.csv(file="FPEO_SA.csv", sep=",")
FPEO_SA <- ts(dat$FPEO_SA, start=c(1994,1), frequency=12)

#Structural Break Identification
bp.FPEO_SA<- breakpoints(FPEO_SA ~ 1)
summary(bp.FPEO_SA)
plot(bp.FPEO_SA)

## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.FPEO_SA)

## confidence intervals
ci.FPEO_SA <- confint(bp.FPEO_SA)
```

```
breakdates(ci.FPEO_SA)
ci.FPEO_SA
plot(FPEO_SA)
lines(ci.FPEO_SA)

##############################################################
                              #(B) Zambian Data
##############################################################
(1) #load Zambia FPEI data and create time series object
dat <- read.csv(file="FPEI_ZM.csv", sep=",")
FPEI_ZM <- ts(dat$FPEI_ZM, start=c(1997,1), frequency=12)

#Structural Break Identification
bp.FPEI_ZM<- breakpoints(FPEI_ZM ~ 1)
summary(bp.FPEI_ZM)
plot(bp.FPEI_ZM)

## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.FPEI_ZM)

## confidence intervals
ci.FPEI_ZM <- confint(bp.FPEI_ZM)
breakdates(ci.FPEI_ZM)
ci.FPEI_ZM
plot(FPEI_ZM)
lines(ci.FPEI_ZM)

#(1b) #load Zambia Log_FPEI data and create time series object
dat <- read.csv(file="Log_FPEI_ZM.csv", sep=",")
log_FPEI_ZM <- ts(dat$Log_FPEI_ZM, start=c(1997,1), frequency=12)

#Structural Break Identification
bp.log_FPEI_ZM<- breakpoints(log_FPEI_ZM ~ 1)
summary(bp.log_FPEI_ZM)
plot(bp.log_FPEI_ZM)

## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.log_FPEI_ZM)

## confidence intervals
ci.log_FPEI_ZM <- confint(bp.log_FPEI_ZM)
breakdates(ci.log_FPEI_ZM)
ci.log_FPEI_ZM
plot(log_FPEI_ZM)
lines(ci.log_FPEI_ZM)

#(2) load Zambia's FPEO data and create time series object
dat <- read.csv(file="FPEO_ZM.csv", sep=",")
FPEO_ZM <- ts(dat$FPEO_ZM, start=c(1997,1), frequency=12)

#Structural Break Identification
bp.FPEO_ZM<- breakpoints(FPEO_ZM ~ 1)
summary(bp.FPEO_ZM)
plot(bp.FPEO_ZM)
```

```
## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.FPEO_ZM)

## confidence intervals
ci.FPEO_ZM <- confint(bp.FPEO_ZM)
breakdates(ci.FPEO_ZM)
ci.FPEO_ZM
plot(FPEO_ZM)
lines(ci.FPEO_ZM)

#(2b) load Zambia's log_FPEO data and create time series object
dat <- read.csv(file="Log_FPEO_ZM.csv", sep=",")
log_FPEO_ZM <- ts(dat$Log_FPEO_ZM, start=c(1997,1), frequency=12)

#Structural Break Identification
bp.log_FPEO_ZM<- breakpoints(log_FPEO_ZM ~ 1)
summary(bp.log_FPEO_ZM)
plot(bp.log_FPEO_ZM)

## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.log_FPEO_ZM)

## confidence intervals
ci.log_FPEO_ZM <- confint(bp.log_FPEO_ZM)
breakdates(ci.log_FPEO_ZM)
ci.log_FPEO_ZM
plot(log_FPEO_ZM)
lines(ci.log_FPEO_ZM)

##############################################################
                                             #(C) Kenyan Data
##############################################################
(1) #load Kenya FPEI data and create time series object
dat <- read.csv(file="FPEI_KN.csv", sep=",")
FPEI_KN <- ts(dat$FPEI_KN, start=c(2011,1), frequency=12)

#Structural Break Identification
bp.FPEI_KN<- breakpoints(FPEI_KN ~ 1)
summary(bp.FPEI_KN)
plot(bp.FPEI_KN)

## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.FPEI_KN)

## confidence intervals
ci.FPEI_KN <- confint(bp.FPEI_KN)
breakdates(ci.FPEI_KN)
ci.FPEI_KN
plot(FPEI_KN)
lines(ci.FPEI_KN)

#(1b) load Kenya Log_FPEI data and create time series object
dat <- read.csv(file="Log_FPEI_KN.csv", sep=",")
```

```
log_FPEI_KN <- ts(dat$Log_FPEI_KN, start=c(2011,1), frequency=12)

#Structural Break Identification
bp.log_FPEI_KN<- breakpoints(log_FPEI_KN ~ 1)
summary(bp.log_FPEI_KN)
plot(bp.log_FPEI_KN)

## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.log_FPEI_KN)

## confidence intervals
ci.log_FPEI_KN<- confint(bp.log_FPEI_KN)
breakdates(ci.log_FPEI_KN)
ci.log_FPEI_KN
plot(log_FPEI_KN)
lines(ci.log_FPEI_KN)

#(2) load Kenya's FPEO data and create time series object
dat <- read.csv(file="FPEO_KN.csv", sep=",")
FPEO_KN <- ts(dat$FPEO_KN, start=c(2011,1), frequency=12)

#Structural Break Identification
bp.FPEO_KN<- breakpoints(FPEO_KN ~ 1)
summary(bp.FPEO_KN)
plot(bp.FPEO_KN)

## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.FPEO_KN)

## confidence intervals
ci.FPEO_KN <- confint(bp.FPEO_KN)
breakdates(ci.FPEO_KN)
ci.FPEO_KN
plot(FPEO_KN)
lines(ci.FPEO_KN)

#(2b) load Kenya's log_FPEO data and create time series object
dat <- read.csv(file="Log_FPEO_KN.csv", sep=",")
log_FPEO_KN <- ts(dat$Log_FPEO_KN, start=c(2011,1), frequency=12)

#Structural Break Identification
bp.log_FPEO_KN<- breakpoints(log_FPEO_KN ~ 1)
summary(bp.log_FPEO_KN)
plot(bp.log_FPEO_KN)

## compute breakdates corresponding to the breakpoints of minimum BIC segmentation
breakdates(bp.log_FPEO_KN)

## confidence intervals
ci.log_FPEO_KN <- confint(bp.log_FPEO_KN)
breakdates(ci.log_FPEO_KN)
ci.log_FPEO_KN
plot(log_FPEO_KN)
lines(ci.log_FPEO_KN)
```

```
########################################################
#(D) Nigerian Data
########################################################
(1) #load Nigeria FPEI data and create time series object
dat <- read.csv(file="FPEI_NG.csv", sep=",")
FPEI_NG <- ts(dat$FPEI_NG, start=c(2013,3), frequency=12)

#Structural Break Identification
bp.FPEI_NG<- breakpoints(FPEI_NG ~ 1)
summary(bp.FPEI_NG)
plot(bp.FPEI_NG)

## compute breakdates corresponding to the
## breakpoints of minimum BIC segmentation
breakdates(bp.FPEI_NG)

## confidence intervals
ci.FPEI_NG <- confint(bp.FPEI_NG)
breakdates(ci.FPEI_NG)
ci.FPEI_NG
plot(FPEI_NG)
lines(ci.FPEI_NG)

#(1b) #load Nigeria Log_FPEI data and create time series object
dat <- read.csv(file="Log_FPEI_NG.csv", sep=",")
log_FPEI_NG <- ts(dat$Log_FPEI_NG, start=c(2013,3), frequency=12)

#Structural Break Identification
bp.log_FPEI_NG<- breakpoints(log_FPEI_NG ~ 1)
summary(bp.log_FPEI_NG)
plot(bp.log_FPEI_NG)

## compute breakdates corresponding to the
## breakpoints of minimum BIC segmentation
breakdates(bp.log_FPEI_NG)

## confidence intervals
ci.log_FPEI_NG<- confint(bp.log_FPEI_NG)
breakdates(ci.log_FPEI_NG)
ci.log_FPEI_NG
plot(log_FPEI_NG)
lines(ci.log_FPEI_NG)

#(2) load Nigeria's FPEO data and create time series object
dat <- read.csv(file="FPEO_NG.csv", sep=",")
FPEO_NG <- ts(dat$FPEO_NG, start=c(2013,3), frequency=12)

#Structural Break Identification
bp.FPEO_NG<- breakpoints(FPEO_NG ~ 1)
summary(bp.FPEO_NG)
plot(bp.FPEO_NG)
```

```
## compute breakdates corresponding to the
## breakpoints of minimum BIC segmentation
breakdates(bp.FPEO_NG)

## confidence intervals
ci.FPEO_NG <- confint(bp.FPEO_NG)
breakdates(ci.FPEO_NG)
ci.FPEO_NG
plot(FPEO_NG)
lines(ci.FPEO_NG)
```

Related to Chapter 4:

A4.1. R Codes for Fractal Signal Classification Estimations

```
## estimating power law coefficients (beta) for Foreign
#equity portfolio flows for South Africa, Zambia Kenya and Nigeria
#By Francis Ziwele Mbao (MBXFRA001), PhD_Finance Student
#University of Cape Town, Department of Finance and Tax

##clear data & close graphs
rm(list=ls())
graphics.off()

## change directory
setwd("~/Documents/Thesis Empirics_Mac/Empirical_Data")
#setwd("C:₩₩Users₩₩image")

#load Package
library("psd")
##########################################################
          ##(1)power law estimation for South Africa's inflows (FPEI) data
##########################################################

#(A) entire sample_FPEI_SA.

# load data and create time series object
dat <- read.csv(file="FPEI_SA.csv", sep=",")
FPEI_SA.tmp <- ts(dat$FPEI_SA, start=c(1994,1), frequency=12)

#model setting
n <- length(FPEI_SA.tmp)
spec <- spectrum(FPEI_SA.tmp, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#Create an object fzmi_0_sa to store values for logfreq & logspec
#for the entire sample
fzmi_0_sa <- lm(logspec ~ logfreq)

#coefficient estimations
b <- coef(fzmi_0_sa)
beta=-b[2]

#plot the logfreq & logspec including line of best fit
plot (logfreq, logspec, type="l")
abline(fzmi_0_sa)

#print the estimated results of beta
print(beta)
##########################################################
```

```
##(B)sub-sample_FPEI_SA_prior to structural break (FPEI_1_SA series).

# load data and create time series object for the sub-sample
dat <- read.csv(file="FPEI_SA.csv", sep=",")
FPEI_SA.tmp <- ts(dat$FPEI_SA, start=c(1994,1), frequency=12)
FPEI_1_SA <- window(FPEI_SA.tmp, start=c(1994,1), end=c(2005,12))

#beta estimation for FPEI_1_SA

n <- length(FPEI_1_SA)
spec <- spectrum(FPEI_1_SA.tmp, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmi_1_sa
fzmi_1_sa <- lm(logspec ~ logfreq)

b <- coef(fzmi_1_sa)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmi_1_sa)
print(beta)
########################################################


##(C)sub-sample_FPEI_SA_after structural break (FPEI_2_SA series).

# load data and create time series object
dat <- read.csv(file="FPEI_SA.csv", sep=",")
FPEI_SA.tmp <- ts(dat$FPEI_SA, start=c(1994,1), frequency=12)
FPEI_2_SA <- window(FPEI_SA.tmp, start=c(2006,2), end=c(2018,4))

#beta estimation for FPI_2_SA

n <- length(FPEI_2_SA)
spec <- spectrum(FPEI_2_SA, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmi_2_sa
fzmi_2_sa <- lm(logspec ~ logfreq)

b <- coef(fzmi_2_sa)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmi_2_sa)
print(beta)
```

```
###########################################################
                  ##(2)power law estimation for South Africa's outflows (FPEO) data
###########################################################

#(A) entire sample_FPEO_SA.

# load data and create time series object
dat <- read.csv(file="FPEO_SA.csv", sep=",")
FPEO_SA.tmp <- ts(dat$FPEO_SA, start=c(1994,1), frequency=12)

#beta estimation for FPO_SA
n <- length(FPEO_SA.tmp)
spec <- spectrum(FPEO_SA.tmp, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmO_0_sa
fzmO_0_sa <- lm(logspec ~ logfreq)

b <- coef(fzmO_0_sa)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmO_0_sa)
print(beta)
###########################################################

##(B)sub-sample_FPO_SA_prior to structural break (FPO_1_SA series).

# load data and create time series object
dat <- read.csv(file="FPEO_SA.csv", sep=",")
FPEO_SA.tmp <- ts(dat$FPEO_SA, start=c(1994,1), frequency=12)
FPEO_1_SA <- window(FPEO_SA.tmp, start=c(1994,1), end=c(2005,12))

#beta estimation for FPEO_1_SA
n <- length(FPEO_1_SA)
spec <- spectrum(FPEO_1_SA, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmO_1_sa
fzmo_1_sa <- lm(logspec ~ logfreq)

b <- coef(fzmo_1_sa)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_1_sa)
print(beta)
###########################################################
```

```
##(C) sub-sample_FPEO_SA_after structural break (FPEO_2_SA series).

# load data and create time series object
dat <- read.csv(file="FPEO_SA.csv", sep=",")
FPEO_SA.tmp <- ts(dat$FPEO_SA, start=c(1994,1), frequency=12)
FPEO_2_SA <- window(FPEO_SA.tmp, start=c(2006,2), end=c(2018,4))

#beta estimation for FPEO_2_SA
n <- length(FPEO_2_SA)
spec <- spectrum(FPEO_2_SA, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmO_2_sa
fzmo_2_sa <- lm(logspec ~ logfreq)

b <- coef(fzmo_2_sa)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_2_sa)
print(beta)
####################################################
                    ##(3)power law estimation of Zambia's inflows (FPEI) data
####################################################

#(A) entire sample_FPE1_ZM.

# load data and create time series object
dat <- read.csv(file="FPEI_ZM.csv", sep=",")
FPEI_ZM.tmp <- ts(dat$FPEI_ZM, start=c(1997,1), frequency=12)

#beta estimation for FPEI_ZM
n <- length(FPEI_ZM.tmp)
spec <- spectrum(FPEI_ZM.tmp, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmi_0_zm
fzmi_0_zm <- lm(logspec ~ logfreq)

b <- coef(fzmi_0_zm)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmi_0_zm)
print(beta)
####################################################
```

```
##(B)sub-sample_FPEI_ZM_prior to structural break (FPEI_1_ZM series).

# load data and create time series object
dat <- read.csv(file="FPEI_ZM.csv", sep=",")
FPEI_ZM.tmp <- ts(dat$FPEI_ZM, start=c(1997,1), frequency=12)
FPEI_1_ZM <- window(FPEI_ZM.tmp, start=c(1997,1), end=c(2005,9))

#beta estimation for FPEI_1_ZM
n <- length(FPEI_1_ZM)
spec <- spectrum(FPEI_1_ZM, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmi_1_sa
fzmi_1_zm <- lm(logspec ~ logfreq)

b <- coef(fzmi_1_zm)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmi_1_zm)
print(beta)
#########################################################


##(C) sub-sample_FPEI_ZM_after structural break (FPEI_2_ZM series).

# load data and create time series object
dat <- read.csv(file="FPEI_ZM.csv", sep=",")
FPEI_ZM.tmp <- ts(dat$FPEI_ZM, start=c(1997,1), frequency=12)
FPEI_2_ZM <- window(FPEI_ZM.tmp, start=c(2005,11), end=c(2018,9))

#beta estimation for FPEI_2_ZM
n <- length(FPEI_2_ZM)
spec <- spectrum(FPEI_2_ZM, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmi_2_zm
fzmi_2_zm <- lm(logspec ~ logfreq)

b <- coef(fzmi_2_zm)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmi_2_zm)
print(beta)

#########################################################
```

```
                    ##(4)power law estimation for Zambia's outflows (FPEO) data
########################################################

#(A) entire sample_FPEO_ZM.

# load data and create time series object
dat <- read.csv(file="FPEO_ZM.csv", sep=",")
FPEO_ZM.tmp <- ts(dat$FPEO_ZM, start=c(1997,1), frequency=12)

#beta estimation for FPEO_0_ZM
n <- length(FPEO_ZM.tmp)
spec <- spectrum(FPEO_ZM.tmp, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmo_0_ZM
fzmo_0_zm <- lm(logspec ~ logfreq)

b <- coef(fzmo_0_zm)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_0_zm)
print(beta)
########################################################

##(B)sub-sample Prior to structural break (FPO_1_ZM series).

# load data and create time series object
dat <- read.csv(file="FPEO_ZM.csv", sep=",")
FPEO_ZM.tmp <- ts(dat$FPEO_ZM, start=c(1997,1), frequency=12)
FPEO_1_ZM <- window(FPEO_ZM.tmp, start=c(1997,1), end=c(2005,9))

#beta estimation for FPEO_1_ZM
n <- length(FPEO_1_ZM)
spec <- spectrum(FPEO_1_ZM, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmo_1_zm
fzmo_1_zm <- lm(logspec ~ logfreq)

b <- coef(fzmo_1_zm)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_1_zm)
print(beta)
########################################################
```

```
##(C)sub-sample_FPO_ZM_after structural break (FPEO_2_ZM series).

# load data and create time series object
dat <- read.csv(file="FPEO_ZM.csv", sep=",")
FPEO_ZM.tmp <- ts(dat$FPEO_ZM, start=c(1997,1), frequency=12)
FPEO_2_ZM <- window(FPEO_ZM.tmp, start=c(2005,11), end=c(2018,9))

#beta estimation for FPEO_2_ZM
n <- length(FPEO_2_ZM)
spec <- spectrum(FPEO_2_ZM, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmo_2_zm
fzmo_2_zm <- lm(logspec ~ logfreq)

b <- coef(fzmo_2_zm)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_2_zm)
print(beta)

#######################################################
                    ##(5)power law estimation of Kenya's inflows (FPEI) data
#######################################################

#(A) entire sample_FPEI_KN.

# load data and create time series object
dat <- read.csv(file="FPEI_KN.csv", sep=",")
FPEI_KN.tmp <- ts(dat$FPEI_KN, start=c(2011,1), frequency=12)

#beta estimation for FPEI_KN
n <- length(FPEI_KN.tmp)
spec <- spectrum(FPEI_KN.tmp, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmi_0_kn
fzmi_0_kn <- lm(logspec ~ logfreq)

b <- coef(fzmi_0_kn)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmi_0_kn)
print(beta)
#######################################################
```

```
##(B)sub-sample_FPEI_KN_after structural break (FPEI_2_KN series).

# load data and create time series object
dat <- read.csv(file="FPEI_KN.csv", sep=",")
FPEI_KN.tmp <- ts(dat$FPEI_KN, start=c(2011,1), frequency=12)
FPEI_2_KN <- window(FPEI_KN.tmp, start=c(2012,9), end=c(2018,9))

#beta estimation for FPEO_2_KN
n <- length(FPEI_2_KN)
spec <- spectrum(FPEI_2_KN, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmi_2_kn
fzmi_2_kn <- lm(logspec ~ logfreq)

b <- coef(fzmi_2_kn)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmi_2_kn)
print(beta)


###################################################
                    ##(6)power law estimation of Kenya's outflows (FPEO) data
###################################################

#(A) entire sample_FPEO_KN.

# load data and create time series object
dat <- read.csv(file="FPEO_KN.csv", sep=",")
FPEO_KN.tmp <- ts(dat$FPEO_KN, start=c(2011,1), frequency=12)

#beta estimation for FPEO_0_KN
n <- length(FPEO_KN.tmp)
spec <- spectrum(FPEO_KN.tmp, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmo_0_kn
fzmo_0_kn <- lm(logspec ~ logfreq)

b <- coef(fzmo_0_kn)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_0_kn)
```

```
print(beta)
##########################################################

##(B)sub-sample_FPEO_KN_after structural break (FPEO_2_KN series).

# load data and create time series object
dat <- read.csv(file="FPEO_KN.csv", sep=",")
FPEO_KN.tmp <- ts(dat$FPEO_KN, start=c(2011,1), frequency=12)
FPEO_2_KN <- window(FPEO_KN.tmp, start=c(2013,2), end=c(2018,9))

#beta estimation for FPEO_2_KN
n <- length(FPEO_2_KN)
spec <- spectrum(FPEO_2_KN, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmo_2_kn
fzmo_2_kn <- lm(logspec ~ logfreq)

b <- coef(fzmo_2_kn)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_2_kn)
print(beta)

##########################################################
            ##(7)power law estimation of Nigeria's inflows (FPEI) data
##########################################################

#(A) entire sample_FPEI_NG.

# load data and create time series object
dat <- read.csv(file="FPEI_NG.csv", sep=",")
FPEI_NG.tmp <- ts(dat$FPEI_NG, start=c(2013,3), frequency=12)

#beta estimation for FPEI_NG
n <- length(FPEI_NG.tmp)
spec <- spectrum(FPEI_NG.tmp, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmi_0_ng
fzmi_0_ng <- lm(logspec ~ logfreq)

b <- coef(fzmi_0_ng)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmi_0_ng)
```

```
print(beta)

#################################################
          ##(8)power law estimation of Nigeria's outflows (FPEO) data
#################################################

#(A) entire sample_FPEO_NG.

# load data and create time series object
dat <- read.csv(file="FPEO_NG.csv", sep=",")
FPEO_NG.tmp <- ts(dat$FPEO_NG, start=c(2013,3), frequency=12)

#beta estimation for FPEO_0_NG
n <- length(FPEO_NG.tmp)
spec <- spectrum(FPEO_NG.tmp, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmo_0_ng
fzmo_0_ng <- lm(logspec ~ logfreq)

b <- coef(fzmo_0_ng)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_0_ng)
print(beta)
#############################################

##(B)sub-sample_FPEO_NG_before structural break (FPEO_2_NG series).
# load data and create time series object
dat <- read.csv(file="FPEO_NG.csv", sep=",")
FPEO_NG.tmp <- ts(dat$FPEO_NG, start=c(2013,3), frequency=12)
FPEO_2_NG <- window(FPEO_NG.tmp, start=c(2013,3), end=c(2015,3))

#beta estimation for FPEO_2_NG
n <- length(FPEO_2_NG)
spec <- spectrum(FPEO_2_NG, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmo_2_ng
fzmo_2_ng <- lm(logspec ~ logfreq)

b <- coef(fzmo_2_ng)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_2_ng)
print(beta)
```

```
##############################################

##(C) sub-sample_FPEO_NG_after structural break (FPEO_2_NG series).

# load data and create time series object
dat <- read.csv(file="FPEO_NG.csv", sep=",")
FPEO_NG.tmp <- ts(dat$FPEO_NG, start=c(2013,3), frequency=12)
FPEO_2_NG <- window(FPEO_NG.tmp, start=c(2015,5), end=c(2019,3))

#beta estimation for FPEO_2_NG
n <- length(FPEO_2_NG)
spec <- spectrum(FPEO_2_NG, detrend=FALSE, demean=TRUE, taper=0)
nr <- (n/2) * (1/8)
specfreq <- spec$freq[1:nr]
specspec <- spec$spec[1:nr]
logfreq <- log(specfreq)
logspec <- log(specspec)

#create object fzmo_2_ng
fzmo_2_ng <- lm(logspec ~ logfreq)

b <- coef(fzmo_2_ng)
beta=-b[2]
plot (logfreq, logspec, type="l")
abline(fzmo_2_ng)
print(beta)
```

A4.2. R Codes for *longmemo* and *somebm* Simulations of FPEFs

```
#Simulations of the fBm and fGn Signals of Foreign Portfolio Equity Flows
                        #for Kenya, Nigeria, South Africa and Zambia
                             #By Francis Ziwele Mbao, MBXFRA001
                                #University of Cape Town
                                  #Department of Finance and Tax

############################################################
############################################################

##set seed number
set.seed(12345)

## House Keeping measures:clear data & close graphs
rm(list=ls())
graphics.off()

##Load packages
library(longmemo) #for fGn signal simulation
library(somebm)  #for fBm signal simulation

                                    #######################
                                         #(1) Inflows
                                   ########################

#1.1 Kenya

#1.1.1 Overall Sample

# Simulations input data: Signal Classification - fGn, Hurst = 0.1074288
plot(simFGN0(500, 0.1074288))

#1.1.2 After the structural Break

# Simulations input data: Signal Classification - Anti-Persistent fBm, Hurst = 0.1031315
plot(fbm(hurst = 0.1031315, n = 500))

#1.2. Nigeria

#1.2.1 Overall Sample

# Simulations input data: Signal Classification - fGn, Hurst = 0.05806095
plot(simFGN0(500, 0.05806095))

#1.3. South Africa

#1.3.1 Overall Sample

# Simulations input data: Signal Classification - Anti-Persistent fBm, Hurst = 0.19052370
plot(fbm(hurst = 0.19052370, n = 500))
```

```
#1.3.2 Before the structural Break

# Simulations input data: Signal Classification – Anti-Persistent fBm, Hurst = 0.2436930
plot(fbm(hurst = 0.2436930, n = 500))

#1.3.3 After the structural Break

# Simulations input data: Signal Classification – fGn, Hurst = 0.09022279
plot(simFGN0(500, 0.09022279))

#1.4. Zambia

#1.4.1 Overall Sample

# Simulations input data: Signal Classification – fGn, Hurst = 0.05406995
plot(simFGN0(500, 0.05406995))

#1.4.2 Before the structural Break

# Simulations input data: Signal Classification – fGn, Hurst = 0.08233582
plot(simFGN0(500, 0.08233582))

#1.4.3 After the structural Break

# Simulations input data: Signal Classification – fGn, Hurst = 0.04051821
plot(simFGN0(500, 0.04051821))
                    ######################
                           #(2) Outflows
                    ######################

#2.1. Kenya

#2.1.1 Overall Sample

# Simulations input data: Signal Classification – fGn, Hurst = 0.1371191
plot(simFGN0(500, 0.1371191))

#2.1.2 After the structural Break

# Simulations input data: Signal Classification – fGn, Hurst = 0.08682716
plot(simFGN0(500, 0.08682716))

#2.2 Nigeria

#2.1 Overall Sample

# Simulations input data: Signal Classification – fGn, Hurst = 0.1509144
plot(simFGN0(500, 0.1509144))

#2.2.2 After the structural Break

# Simulations input data: Signal Classification – persistent fBm, Hurst = 0.1653924
```

```
plot(fbm(hurst = 0.1653924, n = 500))

#2.3. South Africa_Outflows

#2.3.1 Overall Sample

# Simulations input data: Signal Classification – Anti-Persistent fBm, Hurst = 0.1740848
plot(fbm(hurst = 0.1740848, n = 500))

#2.3.2 Before the structural Break

# Simulations input data: Signal Classification – Anti-Persistent fBm, Hurst = 0.205233
plot(fbm(hurst = 0.205233, n = 500))

#2.3.3 After the structural Break

# Simulations input data: Signal Classification – fGn, Hurst = 0.08013597
plot(simFGN0(500, 0.08013597))

#2.4. Zambia

#2.4.1 Overall Sample

# Simulations input data: Signal Classification – fGn, Hurst = 0.05808474
plot(simFGN0(500, 0.05808474))

#2.4.2 Before the structural Break

# Simulations input data: Signal Classification – fGn, Hurst = 0.09229913
plot(simFGN0(500, 0.09229913))

#2.4.3 After the structural Break

# Simulations input data: Signal Classification – fGn, Hurst = 0.06734284
plot(simFGN0(500, 0.06734284))
```

A4.3. R Codes Estimating Long-Range Dependence: The Hurst Exponent

```
## Estimation of the scaling (Hurst) exponent (DFA based) for foreign equity portfolio flows for
                                    #South Africa, Zambia, Kenya and Nigeria
                                     #By Francis Ziwele Mbao (MBXFRA001),
                                         #PhD_Finance Student
                                              #University of Cape Town,
                                                #Department of Finance and Tax

## clear data & close graphs
rm(list=ls())
graphics.off()

## change directory
setwd("~/Documents/Thesis Empirics_Mac/Empirical_Data")

##load Package
library(fractal)

############################################################
                           ##1. estimate Hurst coefficients for South African Data
############################################################

#(A) foreign equity portfolio inflows

#(1)based on the full sample

# load data and create time series object
dat <- read.csv(file="FPEI_SA.csv", sep=",")
FPEI_SA.tmp <- ts(dat$FPEI_SA, start=c(1994,1), frequency=12)

#coefficient estimate
DFA(FPEI_SA.tmp, detrend="poly1", sum.order=0)
############################################################

#(2)#based on the sub-sample before structural break

# load data and create time series object
dat <- read.csv(file="FPEI_SA.csv", sep=",")
FPEI_SA.tmp <- ts(dat$FPEI_SA, start=c(1994,1), frequency=12)
FPEI_1_SA <- window(FPEI_SA.tmp, start=c(1994,1), end=c(2005,12))

#coefficient estimate
DFA(FPEI_1_SA, detrend="poly1", sum.order=0)
############################################################

#(3)#based on the sub-sample after the structural break

# load data and create time series object
dat <- read.csv(file="FPEI_SA.csv", sep=",")
FPEI_SA.tmp <- ts(dat$FPEI_SA, start=c(1994,1), frequency=12)
FPEI_2_SA <- window(FPEI_SA.tmp, start=c(2006,2), end=c(2018,4))
```

```
#coefficient estimate
DFA(FPEI_2_SA, detrend="poly1", sum.order=0)
###############################################################

#(B) foreign equity portfolio outflows

#(1)based on the full sample

# load data and create time series object
dat <- read.csv(file="FPEO_SA.csv", sep=",")
FPEO_SA.tmp <- ts(dat$FPEO_SA, start=c(1994,1), frequency=12)

#coefficient estimate
DFA(FPEO_SA.tmp, detrend="poly1", sum.order=0)
###############################################################

#(2)#based on the sub-sample before structural break

# load data and create time series object
dat <- read.csv(file="FPEO_SA.csv", sep=",")
FPEO_SA.tmp <- ts(dat$FPEO_SA, start=c(1994,1), frequency=12)
FPEO_1_SA <- window(FPEO_SA.tmp, start=c(1994,1), end=c(2005,12))

#coefficient estimate
DFA(FPEO_1_SA, detrend="poly1", sum.order=0)
###############################################################

#(3)#based on the sub-sample after the structural break

# load data and create time series object
dat <- read.csv(file="FPEO_SA.csv", sep=",")
FPEO_SA.tmp <- ts(dat$FPEO_SA, start=c(1994,1), frequency=12)
FPEO_2_SA <- window(FPEO_SA.tmp, start=c(2006,2), end=c(2018,4))

#coefficient estimate
DFA(FPEO_2_SA, detrend="poly1", sum.order=0)
###############################################################

###############################################################
                ##2. estimate Hurst coefficients for Zambian Data
###############################################################

#(A) foreign equity portfolio inflows

#(1)based on the full sample

# load data and create time series object
dat <- read.csv(file="FPEI_ZM.csv", sep=",")
FPEI_ZM.tmp <- ts(dat$FPEI_ZM, start=c(1997,1), frequency=12)

#coefficient estimate
```

```
DFA(FPEI_ZM.tmp, detrend="poly1", sum.order=0)
############################################################

#(2)#based on the sub-sample before structural break

# load data and create time series object
dat <- read.csv(file="FPEI_ZM.csv", sep=",")
FPEI_ZM.tmp <- ts(dat$FPEI_ZM, start=c(1997,1), frequency=12)
FPEI_1_ZM <- window(FPEI_ZM.tmp, start=c(1997,1), end=c(2005,10))

#coefficient estimate
DFA(FPEI_1_ZM, detrend="poly1", sum.order=0)
###########################################################

#(3)#based on the sub-sample after the structural break

# load data and create time series object
dat <- read.csv(file="FPEI_ZM.csv", sep=",")
FPEI_ZM.tmp <- ts(dat$FPEI_ZM, start=c(1997,1), frequency=12)
FPEI_2_ZM <- window(FPEI_ZM.tmp, start=c(2005,12), end=c(2018,9))

#coefficient estimate
DFA(FPEI_2_ZM, detrend="poly1", sum.order=0)
############################################################
#(B) foreign equity portfolio outflows

#(1)based on the full sample

# load data and create time series object
dat <- read.csv(file="FPEO_ZM.csv", sep=",")
FPEO_ZM.tmp <- ts(dat$FPEO_ZM, start=c(1997,1), frequency=12)

#coefficient estimate
DFA(FPEO_ZM.tmp, detrend="poly1", sum.order=0)
############################################################

#(2)#based on the sub-sample before structural break

# load data and create time series object
dat <- read.csv(file="FPEO_ZM.csv", sep=",")
FPEO_ZM.tmp <- ts(dat$FPEO_ZM, start=c(1997,1), frequency=12)
FPEO_1_ZM <- window(FPEO_ZM.tmp, start=c(1997,1), end=c(2006,10))

#coefficient estimate
DFA(FPEO_1_ZM, detrend="poly1", sum.order=0)
############################################################

#(3)#based on the sub-sample after the structural break

# load data and create time series object
dat <- read.csv(file="FPEO_ZM.csv", sep=",")
FPEO_ZM.tmp <- ts(dat$FPEO_ZM, start=c(1997,1), frequency=12)
```

```
FPEO_2_ZM <- window(FPEO_ZM.tmp, start=c(2006,12), end=c(2018,9))

#coefficient estimate
DFA(FPEO_2_ZM, detrend="poly1", sum.order=0)
########################################################

########################################################
                ##3. estimate Hurst coefficients for Kenyan Data
########################################################

#(A) foreign equity portfolio inflows

#(1)based on the full sample

# load data and create time series object
dat <- read.csv(file="FPEI_KN.csv", sep=",")
FPEI_KN.tmp <- ts(dat$FPEI_KN, start=c(2011,1), frequency=12)

#coefficient estimate
DFA(FPEI_KN.tmp, detrend="poly1", sum.order=0)
########################################################

#(3)#based on the sub-sample after the structural break

# load data and create time series object
dat <- read.csv(file="FPEI_KN.csv", sep=",")
FPEI_KN.tmp <- ts(dat$FPEI_KN, start=c(2011,1), frequency=12)
FPEI_2_KN <- window(FPEI_KN.tmp, start=c(2012,9), end=c(2018,9))

#coefficient estimate
DFA(FPEI_2_KN, detrend="poly1", sum.order=0)
########################################################

#(B) foreign equity portfolio outflows

#(1)based on the full sample

# load data and create time series object
dat <- read.csv(file="FPEO_KN.csv", sep=",")
FPEO_KN.tmp <- ts(dat$FPEO_KN, start=c(2011,1), frequency=12)

#coefficient estimate
DFA(FPEO_KN.tmp, detrend="poly1", sum.order=0)
########################################################

#(2)#based on the sub-sample after the structural break

# load data and create time series object
dat <- read.csv(file="FPEO_KN.csv", sep=",")
FPEO_KN.tmp <- ts(dat$FPEO_KN, start=c(2011,1), frequency=12)
FPEO_2_KN <- window(FPEO_KN.tmp, start=c(2012,12), end=c(2018,9))
```

```
#coefficient estimate
DFA(FPEO_2_KN, detrend="poly1", sum.order=0)
##############################################################

##############################################################
##4. estimate Hurst coefficients for Nigerian Data
##############################################################

#(A) foreign equity portfolio inflows

#(1)based on the full sample

# load data and create time series object
dat <- read.csv(file="FPEI_NG.csv", sep=",")
FPEI_NG.tmp <- ts(dat$FPEI_NG, start=c(2013,3), frequency=12)

#coefficient estimate
DFA(FPEI_NG.tmp, detrend="poly1", sum.order=0)
##############################################################

#(B) foreign equity portfolio outflows

#(1)based on the full sample

# load data and create time series object
dat <- read.csv(file="FPEO_NG.csv", sep=",")
FPEO_NG.tmp <- ts(dat$FPEO_NG, start=c(2013,3), frequency=12)

#coefficient estimate
DFA(FPEO_NG.tmp, detrend="poly1", sum.order=0)
##############################################################

#(2a)#based on the sub-sample before the structural break

# load data and create time series object
dat <- read.csv(file="FPEO_NG.csv", sep=",")
FPEO_NG.tmp <- ts(dat$FPEO_NG, start=c(2013,3), frequency=12)
FPEO_2_NG <- window(FPEO_NG.tmp, start=c(2013,3), end=c(2015,3))

#coefficient estimate
DFA(FPEO_2_NG, detrend="poly1", sum.order=0)
##############################################################

#(2b)#based on the sub-sample after the structural break

# load data and create time series object
dat <- read.csv(file="FPEO_NG.csv", sep=",")
FPEO_NG.tmp <- ts(dat$FPEO_NG, start=c(2013,3), frequency=12)
FPEO_2_NG <- window(FPEO_NG.tmp, start=c(2015,5), end=c(2019,3))

#coefficient estimate
DFA(FPEO_2_NG, detrend="poly1", sum.order=0)
```

Related to Chapter 5:

A5.1. Summary Results of Impact Estimation of FPEFs on Stock Market Capitalisation

Table A5.3a: Summary of Response by Variables of Interest Following Shocks to Inflows and Outflows – South Africa

Countries	Variables	Full Sample	After the Structural Break
South Africa	Inflows	Rise for three continuous months with magnitude of 7.0 percent. However, effects decline from the fourth month. Inflows may therefore be anti-persistent due to lack of continuous rise.	Also rise for three consecutive months but relatively less in magnitude at 2.0 percent compared to 7.0 percent for the full sample. The inflows get to the steady state earlier around the 18th month. The attainment of the steady state suggests, therefore that the effect of the shock may not be long lasting.
	Market Capitalisation	Increases for four continuous months, reaching the peak with a 6.0 percent rise by the fourth month following a shock to the inflows. Although the effects decline, market capitalisation does not reach the steady state within two years. Therefore, the effect of the shock could be long lasting.	Relatively less increase compared to the full sample. It rises by 4.0 percent during the peak compared to about 6.0 percent rise in respect of the full sample. Market capitalisation rises for three months compared to four months for full sample. It gets to the steady state, in contrast with the behaviour under the full sample, by the 17th month, an indication that the effect of the shock may not be persistent comparatively.
	Outflows	Only experiences a contemporaneous rise, of about 7.0 percent, but falls subsequently and reaches the steady state by the 13th month. This suggests the effect of a shock to the outflows to be relatively more anti-persistent compared with the inflows.	Also experiences the contemporaneous rise following a shock to itself. However, the rise is less than that of the full sample with a magnitude of 4.0 percent compared to about 7.0 percent in respect of the overall sample. The effects of the shock also die out but much earlier, around the 8th month. Therefore, the effects of the shocks are also not persistent but relatively more anti-persistent when compared to the overall sample.
	Market Capitalisation	Declines for nine continuous months, reaches the lowest around 3.0 percent. It does not get to the steady within two years.	Declines also within three months. However, the magnitude is relatively larger at 4.0 percent. Nonetheless, the effects are not persistent, and the steady state is reached around the 13th month.

Table A5.3b: Summary of Response by Variables of Interest Following Shocks to Inflows and Outflows – Kenya

Countries	Variables	Full Sample	After the Structural Break
Kenya	Inflows	There is only a contemporaneous increase to the inflows following a shock to itself, rising by about 15 percent. Effect of the shock declines from the second month and the inflows get to the steady state by the fourth month. Hence, the effects of the shock may be anti-persistent.	Also experiences the contemporaneous rise following a shock to itself. Nonetheless, this is relatively lower at 6.0 percent with the effects of the shock declining from the second month leading to the inflows reaching the steady state around the sixth month. In this regard, the effects of the shock on the inflows are also likely to be anti-persistent.
	Market Capitalisation	The shock to the inflows leads to market capitalisation rising for three consecutive months with a peak rise of about 1.5 percent. The effects of the shock linger on, extending beyond two years. This suggests the effects of the shock to the FPEI may be persistent on the NSE market capitalisation.	Rises for five continuous months, reaching the peak with a cumulative increase of 3.0 percent. Its effects, nonetheless, dies out in nearly two years after the shock to the inflows. With market capitalisation getting to the steady after the shock, this suggests that the effects of the shock are relatively anti-persistent compared to the case with the overall sample.
	Outflows	A shock to itself results into an increase just on impact with a magnitude of 1.0 percent. However, the effect of the shock declines from the second month with the outflows reaching the steady state around the fifth month. This suggests the effect on the outflows to be anti-persistent like the case is with the inflows.	Increases for two consecutive months, unlike for the overall sample, but with a same magnitude of 1.0 percent. The outflows reach the steady state in the fifth month as well. The effects of the shock to the outflows may be regarded to be anti-persistent given that these effects die out.
	Market Capitalisation	Experiences a rise on impact but declines from the second month and continues till the 11th month. Thereafter, the effects stabilise resulting in market capitalisation failing by about 1.5 percent on impact and continues to about 4.0% where the decline stabilises but not reaching a steady state condition. Therefore, the effect of the shock on market capitalisation may be regarded to be relatively persistent.	Declines also but over two months and thereafter, progressively recovers to reach the steady state around the 14th month. The decline is about 1.0 percent. With the attainment of the steady state condition, the effects of the shock to the outflows on market capitalisation may be regarded to be anti-persistent, unlike the case with the full sample.

Table A5.3c: Summary of Response by Variables of Interest Following Shocks to Inflows and Outflows – Nigeria

Countries	Variables	Full Sample	After the Structural Break
Nigeria	Inflows	There is only a contemporaneous increase to the inflows after a shock to itself and rises for by about 15.0 percent. The effect of the shock declines from the second month and the inflows moves towards the steady state after two years. Hence, the effects of the shock may be relatively anti-persistent.	Not Available
	Market Capitalisation	The shock to the inflows leads to market capitalisation rising for five consecutive months with a 6.0 percent rise on impact and with a peak rise of about 8.0 percent. The effects of the shock do not get to the steady even after two years. This suggests the effects of a shock to the FPEI may be persistent on the NgSE market capitalisation.	Not Available
	Outflows	A shock to itself results into its increase on impact only with a magnitude of 15.0 percent. The effect of the shock fizzles out by the third month as the outflows reaches the steady state. This suggests the effect on the outflows to be relatively more anti-persistent unlike the case with the inflows.	Increases in the first month but with a virtually negligible magnitude, unlike for the overall sample. The outflows reach the steady state in the second month and therefore the effects of the shock to the outflows may be regarded to be anti-persistent.
	Market Capitalisation	Declines for five months with largest level of decline being about 1.0 percent. Thereafter, the effects begins to weaken resulting in market capitalisation reaching the steady state condition by the 16^{th} month. Therefore, the effect of the shock on market capitalisation may be regarded to be short lived and thus may likely be anti-persistent.	Marginally declines over two months but reaches the steady state around the 5th month. The effects of the shock to the outflows on market capitalisation may be regarded to be anti-persistent as well.

Table A5.3d: Summary of Response by Variables of Interest Following Shocks to Inflows and Outflows – Zambia

Countries	Variables	Full Sample	After the Structural Break

Zambia	Inflows	Increases continuously, reaching the peak of 40.0 percent rise by the third month and the declines and remains stable. The effect of the shock may thus be relatively anti-persistent.	Only experiences a contemporaneous increase and then decline thereafter till the 13th month when the effect dies out. This steady state attainment suggests that the effect of the shock makes the flows to be anti-persistent.
	Market Capitalisation	There is only a contemporaneous increase of about 9.0 percent. The effect declines subsequently but lingers on without getting to the steady state within two years, suggesting that the impact of the shock is likely to be persistent.	Also only experiences the contemporaneous rise. However, it is less than that of the full sample with a magnitude of 7.0 percent and therefore being relatively modest compared to the overall sample. The effects of the shock are relatively persistent.
	Outflows	Experiences a contemporaneous rise of over 10 percent. The effects diminish quickly with the outflows getting to the steady state by the third month. The effect of the shock is therefore one that may be regarded to be anti-persistent and in contrast with the way the inflows responds to its own shock.	Increases immediately as well but with a larger magnitude of about 70 percent. However, the effect begins to subside in the second month and reaches the steady state by the fourth month. The effect of the shock is anti-persistent as well just like the case is for the overall sample. It should be noted that the 70 percent shock on the outflows could be related to the Bhatti Airtel mandatory offer of 2010. Bhatti Airtel acquired Zain Zambia, a mobile phone company. In 2008, Zain's IPO involving 22 percent of outstanding shares was open to foreign portfolio investors and whose interest in Zain shares continued in the secondary market following the subsequent listing of the shares on LuSE.
	Market Capitalisation	Declines by about 6.0 percent on impact after a shock to the outflows. However, the effect minimises progressively although market capitalisation does not get to the steady within two years. The effect of the shock on market capitalisation may thus be persistent.	Declines over a period of two months and with a relatively less magnitude of about 4.0 percent. The effect of the shock minimises progressively from the third month although market capitalisation does not reach the steady state. However, the effect of the shock is relatively less persistent compared to the overall sample. In addition, market capitalisation shows signs of convergence to its steady in the period after the structural break than for the overall sample.

A5.2. R Codes for Estimating the Impact of FPEFs on Stock Market Capitalisation

```
#These R Codes create multivariate time series objects for the variables used in the study on the Impact of #Foreign Portfolio Equity Flows on Stock Market Capitalisation.

## clear data & close graphs
rm(list=ls())
graphics.off()

set.seed(12345)
library(VARsignR)

#set working directory
#getwd()
setwd("~/Documents/Thesis Empirics_Mac/Empirical_Data")

############################################################
                    #1.  South African Data
            ######################################
                   #  Inflows-Overall Sample
 ##########################################################

# load data and create time series object
#(i) load South Africa FPEI data and create time series object
dat <- read.csv(file="Log_FPEI_SA_sa.csv", sep=",")
FPEI_SA_sa <- ts(dat$Log_FPEI_SA_sa, start=c(1994,1), frequency=12)

#(iia) load data and create time series object for SA_JSEMCap
dat <- read.csv(file="Log_JSEMcap_SA_sa.csv", sep=",")
JSEMCap_sa<- ts(dat$Log_JSEMcap_SA_sa, start=c(1994,1), frequency=12)

#(iib) load data and create time series object for SA_JSEMCap
dat <- read.csv(file="Log_JSEMcapR_sa.csv", sep=",")
     JSEMCapR_sa<- ts(dat$Log_JSEMcapR_sa, start=c(1994,1), frequency=12)

#(iii) load data and create time series object for SA_PVMP
dat <- read.csv(file="Log_PVMP_SA_sa.csv", sep=",")
PVMP_sa<- ts(dat$Log_PVMP_SA_sa, start=c(1994,1), frequency=12)

#(iv) load data and create time series object for JSE_Domestic_Turnover
dat <- read.csv(file="Log_JSEDTO_sa.csv", sep=",")
JSEDTO_sa<- ts(dat$Log_JSEDTO_sa, start=c(1994,1), frequency=12)

#(v) load data and create time series object for SA_Exchange Rate
dat <- read.csv(file="Log_EXR_SA_sa.csv", sep=",")
EXR_SA_sa<- ts(dat$Log_EXR_SA_sa, start=c(1994,1), frequency=12)

#(vi) load data and create time series object for SA_Inflation
dat <- read.csv(file="Inf_SA_sa.csv", sep=",")
Inf_SA_sa<- ts(dat$Inf_SA_sa, start=c(1994,1), frequency=12)

#merge the data set into a dataframe for FPEI Impact on JES MktCap
```

```
SA_DB_sa = cbind(FPEI_SA_sa, JSEMCap_sa, PVMP_sa, EXR_SA_sa, Inf_SA_sa, JSEDTO_sa)
varnames <- colnames(SA_DB_sa)

#(1a) Impact of Positive FPEI Shock on JSE Market Capitalisation

#Imposing Restrictions
 constr <- c(+1, +2)

set.seed(12345)

#(1)MCMC based on the Uhlig (2005) Penalty Method
fpei_sa_mod_sa <- uhlig.penalty(Y=SA_DB_sa, nlags=2, draws=500, subdraws=500,
nkeep=1000, KMIN=1,
                    KMAX=6, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_sa <- fpei_sa_mod_sa$IRFS

vl <- c("Inflows","JSE Market Capitalisation","PVMP", "Exchange Rate", "Headline Inflation", "JSE
Market Turnover")

irfplot(irfdraws=irfs1_sa, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                        grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=SA_DB_sa, irfdraws=irfs1_sa, nlags =2, constant = T, labels = vl, target = TRUE,
                         type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE,
bw=FALSE,
                         legend = TRUE, maxit = 1000)

                              ########################
                                 # Inflows-After Structural Break
                              ########################

#(1b) Impact of Positive FPEI Shock on JSE Market Capitalisation After Structural Break

#(i) load data and create time series object FOR SA_FPEI
dat <- read.csv(file="Log_FPEI_SA_sa.csv", sep=",")
FPEI_SA_sa <- ts(dat$Log_FPEI_SA_sa, start=c(1994,1), frequency=12)
FPEI_SA_sa_asb <- window(FPEI_SA_sa, start=c(2006,2), end=c(2018,4))

#(ii) load data and create time series object FOR SA_JSEMCap
dat <- read.csv(file="Log_JSEMcap_SA_sa.csv", sep=",")
JSEMCap_sa<- ts(dat$Log_JSEMcap_SA_sa, start=c(1994,1), frequency=12)
JSEMCap_sa_asb <- window(JSEMCap_sa, start=c(2006,2), end=c(2018,4))

#(iii) load data and create time series object FOR SA_PVMP
dat <- read.csv(file="Log_PVMP_SA_sa.csv", sep=",")
PVMP_sa<- ts(dat$Log_PVMP_SA_sa, start=c(1994,1), frequency=12)
PVMP_sa_asb <- window(PVMP_sa, start=c(2006,2), end=c(2018,4))

#(iv) load data and create time series object FOR JSE_Domestic_Turnover
```

```
dat <- read.csv(file="Log_JSEDTO_sa.csv", sep=",")
JSEDTO_sa<- ts(dat$Log_JSEDTO_sa, start=c(1994,1), frequency=12)
JSEDTO_sa_asb <- window(JSEDTO_sa, start=c(2006,2), end=c(2018,4))

#(v) load data and create time series object for SA_Exchange Rate
dat <- read.csv(file="Log_EXR_SA_sa.csv", sep=",")
EXR_SA_sa<- ts(dat$Log_EXR_SA_sa, start=c(1994,1), frequency=12)
EXR_SA_sa_asb <- window(EXR_SA_sa, start=c(2006,2), end=c(2018,4))

#(vi) load data and create time series object FOR SA_Inflation
dat <- read.csv(file="Inf_SA_sa.csv", sep=",")
Inf_SA_sa<- ts(dat$Inf_SA_sa, start=c(1994,1), frequency=12)
Inf_SA_sa_asb <- window(Inf_SA_sa, start=c(2006,2), end=c(2018,4))

#merge the data set into a dataframe for FPEI Impact on JES MktCap
SA_DB_sa_asb = cbind(FPEI_SA_sa_asb, JSEMCap_sa_asb, PVMP_sa_asb, EXR_SA_sa_asb,
Inf_SA_sa_asb,
                     JSEDTO_sa_asb)

varnames <- colnames(SA_DB_sa_asb)

#Imposing Restrictions
constr <- c(+1, +2)

set.seed(12345)

#(2)MCMC based on the Uhlig (2005) Penalty Method
fpei_sa_mod_sa_asb <- uhlig.penalty(Y=SA_DB_sa_asb, nlags=1, draws=500, subdraws=500,
nkeep=1000,
                       KMIN=1, KMAX=12, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_sa_asb <- fpei_sa_mod_sa_asb$IRFS

vl <- c("Inflows","JSE Market Capitalisation","PVMP", "Exchange Rate", "Headline Inflation", "JSE
Market Turnover")

irfplot(irfdraws=irfs1_sa_asb, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                     grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
 fp.target(Y=SA_DB_sa_asb, irfdraws=irfs1_sa_asb, nlags = 1, constant = T, labels = vl, target =
TRUE,
                     type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                     legend = TRUE, maxit = 1000)

                     ##################################
                                #Outflows-Overall Sample
                     ##################################

#(2a) Estimating impact of Positive Shock to Portfolio equity outflows on JSE Market Cap
```

```
#(1) Loading data and create time series object for FPEO_SA
dat <- read.csv(file="Log_FPEO_SA_sa.csv", sep=",")
FPEO_SA_sa <- ts(dat$Log_FPEO_SA_sa, start=c(1994,1), frequency=12)

#merge the data set into a dataframe
DB_SA_sa = cbind(FPEO_SA_sa, JSEMCap_sa, PVMP_sa, EXR_SA_sa, Inf_SA_sa, JSEDTO_sa)
varnames <- colnames(DB_SA_sa)

#Imposing Restrictions
constr <- c(+1, +4, +5, +6)

set.seed(12345)

#(2)MCMC based on the Uhlig (2005) Penalty Method
 fpeo_sa_mod_sa <- uhlig.penalty(Y=DB_SA_sa, nlags=2, draws=800, subdraws=800,
nkeep=1000,
                    KMIN=1, KMAX=12, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs2_sa <- fpeo_sa_mod_sa$IRFS

v2 <- c("Outflows","JSE Market Capitalisation","PVMP", "Exchange Rate", "Headline Inflation",
"JSE Market Turnover")

irfplot(irfdraws=irfs2_sa, type="median", labels=v2, save=FALSE, bands=c(0.16, 0.84),
                     grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=DB_SA_sa, irfdraws=irfs2_sa, nlags = 2, constant = T, labels = v2, target = TRUE,
                     type = "median", bands=c(0.16, 0.84), save=FALSE, grid=TRUE, bw=FALSE,
                     legend = TRUE, maxit = 1000)

                         ####################################
                                 #Outflows-After Structural Break
                         ####################################

#(i) load data and create time series object for SA_FPEI After Structural Break
dat <- read.csv(file="Log_FPEO_SA_sa.csv", sep=",")
FPEO_SA_sa <- ts(dat$Log_FPEO_SA_sa, start=c(1994,1), frequency=12)
FPEO_SA_sa_asb <- window(FPEO_SA_sa, start=c(2006,2), end=c(2018,4))

#(ii) load data and create time series object for SA_JSEMCap
dat <- read.csv(file="Log_JSEMcap_SA_sa.csv", sep=",")
JSEMCap_sa<- ts(dat$Log_JSEMcap_SA_sa, start=c(1994,1), frequency=12)
JSEMCap_sa_asb <- window(JSEMCap_sa, start=c(2006,2), end=c(2018,4))

#(iii) load data and create time series object for SA_PVMP
dat <- read.csv(file="Log_PVMP_SA_sa.csv", sep=",")
PVMP_sa<- ts(dat$Log_PVMP_SA_sa, start=c(1994,1), frequency=12)
PVMP_sa_asb <- window(PVMP_sa, start=c(2006,2), end=c(2018,4))

#(iv) load data and create time series object for JSE_Domestic_Turnover
```

```
dat <- read.csv(file="Log_JSEDTO_sa.csv", sep=",")
JSEDTO_sa<- ts(dat$Log_JSEDTO_sa, start=c(1994,1), frequency=12)
JSEDTO_sa_asb <- window(JSEDTO_sa, start=c(2006,2), end=c(2018,4))

#(v) load data and create time series object for SA_Exchange Rate
dat <- read.csv(file="Log_EXR_SA_sa.csv", sep=",")
EXR_SA_sa<- ts(dat$Log_EXR_SA_sa, start=c(1994,1), frequency=12)
EXR_SA_sa_asb <- window(EXR_SA_sa, start=c(2006,2), end=c(2018,4))

#(vi) load data and create time series object for SA_Inflation
 dat <- read.csv(file="Inf_SA_sa.csv", sep=",")
Inf_SA_sa<- ts(dat$Inf_SA_sa, start=c(1994,1), frequency=12)
Inf_SA_sa_asb <- window(Inf_SA_sa, start=c(2006,2), end=c(2018,4))

#merge the data set into a dataframe for FPEI Impact on JES MktCap
SA_DB_sa_asb = cbind(FPEO_SA_sa_asb,  JSEMCap_sa_asb, PVMP_sa_asb, EXR_SA_sa_asb,
Inf_SA_sa_asb, JSEDTO_sa_asb)
varnames <- colnames(SA_DB_sa_asb)

#(2b) Impact of Positive Shock to the FPEO on JSE Market Capitalisation After Structural Break

#Imposing Restrictions
constr <- c(+1, +4)

 set.seed(12345)

#MCMC based on the Uhlig (2005) Penalty Method
fpeo_sa_mod_sa_asb <- uhlig.penalty(Y=SA_DB_sa_asb, nlags= 1, draws=800, subdraws=800,
nkeep=1000,
                              KMIN=1, KMAX=12, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_sa_asb <- fpeo_sa_mod_sa_asb$IRFS

vl <- c("Outflows","JSE Market Capitalisation", "PVMP", "Exchange Rate", "Headline Inflation",
"JSE Market Turnover")

irfplot(irfdraws=irfs1_sa_asb, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                            grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=SA_DB_sa_asb, irfdraws=irfs1_sa_asb, nlags = 1, constant = T, labels = vl, target =
TRUE,
                         type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                         legend = TRUE, maxit = 1000)

##############################################################
                                   #Zambian Data
             ##############################################
                                #Inflows-Overall Sample
                   ##################################

# load data and create time series object
```

```
#(i) load Zambia's FPEI data and create time series object
dat <- read.csv(file="Log_FPEI_ZM_sa.csv", sep=",")
FPEI_ZM_sa <- ts(dat$Log_FPEI_ZM_sa, start=c(1997,1), frequency=12)

#(ii) load data and create time series object for LuSE Market Capitalisation
dat <- read.csv(file="Log_LuSEMktCap_sa.csv", sep=",")
LuSEMCap_sa<- ts(dat$Log_LuSEMktCap_sa, start=c(1997,1), frequency=12)

#(iii) load data and create time series object for Real Private Sector Credit
dat <- read.csv(file="Log_RPSC_ZM_sa.csv", sep=",")
RPSC_sa<- ts(dat$Log_RPSC_ZM_sa, start=c(1997,1), frequency=12)

#(iv) load data and create time series object for LuSE_Market_Turnover
dat <- read.csv(file="Log_LuSEMTO_sa.csv", sep=",")
LuSEMTO_sa<- ts(dat$Log_LuSEMTO_sa, start=c(1997,1), frequency=12)

#(v) load data and create time series object for Zambia_Exchange Rate
dat <- read.csv(file="Log_EXR_ZM_sa.csv", sep=",")
EXR_ZM_sa<- ts(dat$Log_EXR_ZM_sa, start=c(1997,1), frequency=12)

#(vi) load data and create time series object for Zambia_Headline Inflation
dat <- read.csv(file="Inf_ZM_sa.csv", sep=",")
Inf_ZM_sa<- ts(dat$Inf_ZM_sa, start=c(1997,1), frequency=12)

#merge the data set into a dataframe for FPEI Impact on LuSE MktCap
ZM_DB_sa = cbind(FPEI_ZM_sa, LuSEMCap_sa, RPSC_sa, EXR_ZM_sa, Inf_ZM_sa,
LuSEMTO_sa)
varnames <- colnames(ZM_DB_sa)

#(3a) #Impact of Positive FPEI Shock on LuSE Market Capitalisation

#Imposing Restrictions
constr <- c(+1, +2, -4)

set.seed(12345)

#MCMC based on the Uhlig (2005) Penalty Method
fpei_zm_mod_sa <- uhlig.penalty(Y=ZM_DB_sa, nlags=2, draws=800, subdraws=800,
nkeep=1000,
                              KMIN=1, KMAX=6, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_zm<- fpei_zm_mod_sa$IRFS

vl <- c("Inflows","LuSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"LuSE Market Turnover")

irfplot(irfdraws=irfs1_zm, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                          grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=ZM_DB_sa, irfdraws=irfs1_zm, nlags =2, constant = T, labels = vl, target = TRUE,
```

```
                  type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                  legend = TRUE, maxit = 1000)

                         ################################
                               #Inflows-After Structural Break
                         #################################

#(i) load data and create time series object for Zambia FPEI After Structural Break
dat <- read.csv(file="Log_FPEI_ZM_sa.csv", sep=",")
FPEI_ZM_sa <- ts(dat$Log_FPEI_ZM_sa, start=c(1997,1), frequency=12)
FPEI_ZM_sa_asb <- window(FPEI_ZM_sa, start=c(2005,11), end=c(2018,9))

#(ii) load data and create time series object FOR LuSE Market Cap
dat <- read.csv(file="Log_LuSEMktCap_sa.csv", sep=",")
LuSEMCap_sa<- ts(dat$Log_LuSEMktCap_sa, start=c(1997,1), frequency=12)
LuSEMCap_sa_asb <- window(LuSEMCap_sa, start=c(2005,11), end=c(2018,9))

#(iii) load data and create time series object for Real Private Sector Credit
dat <- read.csv(file="Log_RPSC__ZM_sa.csv", sep=",")
RPSC_sa<- ts(dat$Log_RPSC_ZM_sa, start=c(1997,1), frequency=12)
RPSC_sa_asb <- window(RPSC_sa, start=c(2005,11), end=c(2018,9))

#(iv) load data and create time series object for LuSE Market Turnover
dat <- read.csv(file="Log_LuSEMTO_sa.csv", sep=",")
LuSEMTO_sa<- ts(dat$Log_LuSEMTO_sa, start=c(1997,1), frequency=12)
LuSEMTO_sa_asb <- window(LuSEMTO_sa, start=c(2005,11), end=c(2018,9))

#(v) load data and create time series object for Zambia's Exchange Rate
dat <- read.csv(file="Log_EXR_ZM_sa.csv", sep=",")
EXR_ZM_sa<- ts(dat$Log_EXR_ZM_sa, start=c(1997,1), frequency=12)
EXR_ZM_sa_asb <- window(EXR_ZM_sa, start=c(2005,11), end=c(2018,9))

#(vi) load data and create time series object for Zambia's Headline Inflation
dat <- read.csv(file="Inf_ZM_sa.csv", sep=",")
Inf_ZM_sa<- ts(dat$Inf_ZM_sa, start=c(1997,1), frequency=12)
Inf_ZM_sa_asb <- window(Inf_ZM_sa, start=c(2005,11), end=c(2018,9))

#merge the data set into a dataframe for FPEI Impact on LuSE MktCap
ZM_DB_sa_asb = cbind(FPEI_ZM_sa_asb, LuSEMCap_sa_asb, RPSC_sa_asb, EXR_ZM_sa_asb,
Inf_ZM_sa_asb, LuSEMTO_sa_asb)

varnames <- colnames(ZM_DB_sa_asb)

#(3b) Impact of Positive Shock to FPEI on LuSE Market Capitalisation After Structural Break

#Imposing Restrictions
constr <- c(+1, +2)

set.seed(12345)
#(2)MCMC based on the Uhlig (2005) Rejection Method

fpei_zm_mod_sa_asb <- uhlig.penalty(Y=ZM_DB_sa_asb, nlags=1, draws=800, subdraws=800,
```

```
                  nkeep=1000, KMIN=1, KMAX=6, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_sa_asb <- fpei_zm_mod_sa_asb$IRFS

vl <- c("Inflows","LuSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"LuSE Market Turnover")

irfplot(irfdraws=irfs1_sa_asb, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                             grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=ZM_DB_sa_asb, irfdraws=irfs1_sa_asb, nlags = 1, constant = T, labels = vl, target =
TRUE,
                         type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                         legend = TRUE, maxit = 1000)

                            ######################################
                                        #Outflows-Overall Sample
                          #######################################

#(4a)Estimating impact of Positive Shock to Portfolio equity outflows on LuSE Market Cap

#(1) Loading data and create time series object for FPEO_ZM
dat <- read.csv(file="Log_FPEO_ZM_sa.csv", sep=",")
FPEO_ZM_sa <- ts(dat$Log_FPEO_ZM_sa, start=c(1997,1), frequency=12)

#merge the data set into a dataframe for FPEO Impact on LuSE MktCap
ZM_BD_sa = cbind(FPEO_ZM_sa, LuSEMCap_sa, RPSC_sa, EXR_ZM_sa, Inf_ZM_sa,
LuSEMTO_sa)

varnames <- colnames(ZM_BD_sa)

#Imposing Restrictions
constr <- c(+1, +4, +5)

set.seed(12345)
#MCMC based on the Uhlig (2005) Penalty Method

fpeo_zm_mod_sa <- uhlig.penalty(Y=ZM_BD_sa, nlags=1, draws=800, subdraws=800,
nkeep=1000,
                         KMIN=1, KMAX=6, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_zm<- fpeo_zm_mod_sa$IRFS

vl <- c("Outflows","LuSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"LuSE Market Turnover")

irfplot(irfdraws=irfs1_zm, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                    grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
```

```
fp.target(Y=ZM_BD_sa, irfdraws=irfs1_zm, nlags =1, constant = T, labels = vl, target = TRUE,
                    type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                    legend = TRUE, maxit = 1000)

          ##################################################
                              #Outflows-After Structural Break
          ##################################################

#(i) load data and create time series object for Zambia FPEO After Structural Break
dat <- read.csv(file="Log_FPEO_ZM_sa.csv", sep=",")
FPEO_ZM_sa <- ts(dat$Log_FPEO_ZM_sa, start=c(1997,1), frequency=12)
FPEO_ZM_sa_asb <- window(FPEO_ZM_sa, start=c(2006,12), end=c(2018,9))

#(ii) load data and create time series object for LuSE Market Cap
dat <- read.csv(file="Log_LuSEMktCap_sa.csv", sep=",")
LuSEMCap_sa<- ts(dat$Log_LuSEMktCap_sa, start=c(1997,1), frequency=12)
LuSEMCap_sa_asb <- window(LuSEMCap_sa, start=c(2006,12), end=c(2018,9))

#(iii) load data and create time series object for Real Private Sector Credit
dat <- read.csv(file="Log_RPSC_ZM_sa.csv", sep=",")
RPSC_sa<- ts(dat$Log_RPSC_ZM_sa, start=c(1997,1), frequency=12)
RPSC_sa_asb <- window(RPSC_sa, start=c(2006,12), end=c(2018,9))

#(iv) load data and create time series object FOR LuSE Market Turnover
dat <- read.csv(file="Log_LuSEMTO_sa.csv", sep=",")
LuSEMTO_sa<- ts(dat$Log_LuSEMTO_sa, start=c(1997,1), frequency=12)
LuSEMTO_sa_asb <- window(LuSEMTO_sa, start=c(2006,12), end=c(2018,9))

#(v) load data and create time series object for Zambia's Exchange Rate
dat <- read.csv(file="Log_EXR_ZM_sa.csv", sep=",")
EXR_ZM_sa<- ts(dat$Log_EXR_ZM_sa, start=c(1997,1), frequency=12)
EXR_ZM_sa_asb <- window(EXR_ZM_sa, start=c(2006,12), end=c(2018,9))

#(vi) load data and create time series object for Zambia's Headline Inflation
dat <- read.csv(file="Inf_ZM_sa.csv", sep=",")
Inf_ZM_sa<- ts(dat$Inf_ZM_sa, start=c(1997,1), frequency=12)
Inf_ZM_sa_asb <- window(Inf_ZM_sa, start=c(2006,12), end=c(2018,9))

#merge the data set into a dataframe for FPEI Impact on LuSE MktCap
ZM_DF_sa_asb = cbind(FPEO_ZM_sa_asb, LuSEMCap_sa_asb, RPSC_sa_asb, EXR_ZM_sa_asb,
Inf_ZM_sa_asb,LuSEMTO_sa_asb)

varnames <- colnames(ZM_DF_sa_asb)

#(4b) Impact of Positive Shock to FPEO on LuSE Market Capitalisation After Structural Break

#Imposing Restrictions
constr <- c(+1, +4, +5)

set.seed(12345)
#MCMC based on the Uhlig (2005) Penalty Method
fpeo_zm_mod_sa_asb <- uhlig.penalty(Y=ZM_DF_sa_asb, nlags=2, draws=800, subdraws=800,
```

```
                nkeep=1000, KMIN=1, KMAX=12, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_sa_asb <- fpeo_zm_mod_sa_asb$IRFS

vl <- c("Outflows","LuSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"LuSE Market Turnover")

irfplot(irfdraws=irfs1_sa_asb, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                        grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=ZM_DF_sa_asb, irfdraws=irfs1_sa_asb, nlags = 2, constant = T, labels = vl, target =
TRUE,
                     type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                     legend = TRUE, maxit = 1000)

#######################################################
                                    ##Kenyan Data
          ##############################################
                                #Inflows-Overall Sample
                     ####################################

# load data and create time series object
#(i) load Kenya's FPEI data and create time series object
dat <- read.csv(file="Log_FPEI_KN_sa.csv", sep=",")
FPEI_KN_sa <- ts(dat$Log_FPEI_KN_sa, start=c(2011,1), frequency=12)

#(ii) load data and create time series object for NSE Market Capitalisation
dat <- read.csv(file="Log_NSEMCap_sa.csv", sep=",")
NSEMCap_sa<- ts(dat$Log_NSEMCap_sa, start=c(2011,1), frequency=12)

#(iii) load data and create time series object for Real PSC
dat <- read.csv(file="Log_RPSC_KN_sa.csv", sep=",")
RPSC_KN_sa<- ts(dat$Log_RPSC_KN_sa, start=c(2011,1), frequency=12)

#(iv) load data and create time series object FOR NSE_Market_Turnover
dat <- read.csv(file="Log_NSEMTO_sa.csv", sep=",")
NSEMTO_sa<- ts(dat$Log_NSEMTO_sa, start=c(2011,1), frequency=12)

#(v) load data and create time series object for Kenya_Exchange Rate
dat <- read.csv(file="Log_EXR_KN_sa.csv", sep=",")
EXR_KN_sa<- ts(dat$Log_EXR_KN_sa, start=c(2011,1), frequency=12)

#(vi) load data and create time series object for Kenya Inflation
dat <- read.csv(file="Inf_KN_sa.csv", sep=",")
Inf_KN_sa<- ts(dat$Inf_KN_sa, start=c(2011,1), frequency=12)

#merge the data set into a dataframe for FPEI Impact on NSE MktCap
KN_DB_sa = cbind(FPEI_KN_sa, NSEMCap_sa, RPSC_KN_sa, EXR_KN_sa, Inf_KN_sa,
NSEMTO_sa)

varnames <- colnames(KN_DB_sa)
```

```
#(3a) #Impact of Positive FPEI Shock on NSE Market Capitalisation

#Imposing Restrictions
constr <- c(+1, +2)

set.seed(12345)

#MCMC based on the Uhlig (2005) Penalty Method
fpei_kn_mod_sa <- uhlig.penalty(Y=KN_DB_sa, nlags=1, draws=800, subdraws=800,
nkeep=1000,
                    KMIN=1, KMAX=6, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_kn<- fpei_kn_mod_sa$IRFS

vl <- c("Inflows","NSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"NSE Market Turnover")

irfplot(irfdraws=irfs1_kn, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                     grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=KN_DB_sa, irfdraws=irfs1_kn, nlags =1, constant = T, labels = vl, target = TRUE,
                    type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                    legend = TRUE, maxit = 1000)

            ##############################################
                         #Inflows-After Structural Break
            ##############################################

#(i) load data and create time series object for Kenya FPEI After Structural Break
dat <- read.csv(file="Log_FPEI_KN_sa.csv", sep=",")
FPEI_KN_sa <- ts(dat$Log_FPEI_KN_sa, start=c(2011,1), frequency=12)
FPEI_KN_sa_asb <- window(FPEI_KN_sa, start=c(2012,9), end=c(2018,9))

#(ii) load data and create time series object for the NSE Market Cap
dat <- read.csv(file="Log_NSEMCap_sa.csv", sep=",")
NSEMCap_sa<- ts(dat$Log_NSEMCap_sa, start=c(2011,1), frequency=12)
NSEMCap_sa_asb <- window(NSEMCap_sa, start=c(2012,9), end=c(2018,9))

#(iii) load data and create time series object for Real Private Sector Credit
dat <- read.csv(file="Log_RPSC_KN_sa.csv", sep=",")
RPSC_KN_sa<- ts(dat$Log_RPSC_KN_sa, start=c(2011,1), frequency=12)
RPSC_KN_sa_asb <- window(RPSC_KN_sa, start=c(2012,9), end=c(2018,9))

#(iv) load data and create time series object FOR NSE Market Turnover
dat <- read.csv(file="Log_NSEMTO_sa.csv", sep=",")
NSEMTO_sa<- ts(dat$Log_NSEMTO_sa, start=c(2011,1), frequency=12)
NSEMTO_sa_asb <- window(NSEMTO_sa, start=c(2012,9), end=c(2018,9))

#(v) load data and create time series object for Kenya's Exchange Rate
```

```
dat <- read.csv(file="Log_EXR_KN_sa.csv", sep=",")
EXR_KN_sa<- ts(dat$Log_EXR_KN_sa, start=c(2011,1), frequency=12)
EXR_KN_sa_asb <- window(EXR_KN_sa, start=c(2012,9), end=c(2018,9))

#(vi) load data and create time series object for Kenya's Inflation
dat <- read.csv(file="Inf_KN_sa.csv", sep=",")
Inf_KN_sa<- ts(dat$Inf_KN_sa, start=c(2011,1), frequency=12)
Inf_KN_sa_asb <- window(Inf_KN_sa, start=c(2012,9), end=c(2018,9))

#merge the data set into a dataframe for FPEI Impact on NSE MktCap
KN_DB_sa_asb = cbind(FPEI_KN_sa_asb, NSEMCap_sa_asb, RPSC_KN_sa_asb,
EXR_KN_sa_asb, Inf_KN_sa_asb, NSEMTO_sa_asb)

varnames <- colnames(KN_DB_sa_asb)

#(3b) Impact of Positive Shock to FPEI on NSE Market Capitalisation After Structural Break

#Imposing Restrictions
constr <- c(+1, +2)

set.seed(12345)
#(2)MCMC based on the Uhlig (2005) Rejection Method

fpei_kn_mod_sa_asb <- uhlig.penalty(Y=KN_DB_sa_asb, nlags=1, draws=800, subdraws=800,
nkeep=1000,
                        KMIN=1, KMAX=6, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_sa_asb <- fpei_kn_mod_sa_asb$IRFS

vl <- c("Inflows","NSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"NSE Market Turnover")

irfplot(irfdraws=irfs1_sa_asb, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                         grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=KN_DB_sa_asb, irfdraws=irfs1_sa_asb, nlags = 1, constant = T, labels = vl, target =
TRUE,
                        type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                        legend = TRUE, maxit = 1000)

              ################################################
                              #Outflows-Overall Sample
             #################################################

#(4a)Estimating impact of Positive Shock to Portfolio equity outflows on NSE Market Cap

#(1) Loading data and create time series object for FPEO_KN
dat <- read.csv(file="Log_FPEO_KN_sa.csv", sep=",")
FPEO_KN_sa <- ts(dat$Log_FPEO_KN_sa, start=c(2011,1), frequency=12)
```

```
#merge the data set into a dataframe for FPEO Impact on NSE MktCap
KN_BD_sa = cbind(FPEO_KN_sa, NSEMCap_sa, RPSC_KN_sa, EXR_KN_sa, Inf_KN_sa,
NSEMTO_sa)

varnames <- colnames(KN_BD_sa)

#Imposing Restrictions
constr <- c(+1, +4)

set.seed(12345)
#MCMC based on the Uhlig (2005) Penalty Method

fpeo_kn_mod_sa <- uhlig.penalty(Y=KN_BD_sa, nlags=1, draws=800, subdraws=800,
nkeep=1000,
                    KMIN=1, KMAX=6, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_kn<- fpeo_kn_mod_sa$IRFS

vl <- c("Outflows","NSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"NSE Market Turnover")

irfplot(irfdraws=irfs1_kn, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                    grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=KN_BD_sa, irfdraws=irfs1_kn, nlags =1, constant = T, labels = vl, target = TRUE,
                    type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                    legend = TRUE, maxit = 1000)

                    #########################################
                                #Outflows-After Structural Break
                    #########################################

#(i) load data and create time series object for Kenya FPEO After Structural Break
dat <- read.csv(file="Log_FPEO_KN_sa.csv", sep=",")
FPEO_KN_sa <- ts(dat$Log_FPEO_KN_sa, start=c(2011,1), frequency=12)
FPEO_KN_sa_asb <- window(FPEO_KN_sa, start=c(2013,2), end=c(2018,9))

#(ii) load data and create time series object for NSE Market Cap
dat <- read.csv(file="Log_NSEMCap_sa.csv", sep=",")
NSEMCap_sa<- ts(dat$Log_NSEMCap_sa, start=c(2011,1), frequency=12)
NSEMCap_sa_asb <- window(NSEMCap_sa, start=c(2013,2), end=c(2018,9))

#(iii) load data and create time series object for Real Private Sector Credit
dat <- read.csv(file="Log_RPSC_KN_sa.csv", sep=",")
RPSC_KN_sa<- ts(dat$Log_RPSC_KN_sa, start=c(2011,1), frequency=12)
RPSC_KN_sa_asb <- window(RPSC_KN_sa, start=c(2013,2), end=c(2018,9))

#(iv) load data and create time series object for NSE Market Turnover
dat <- read.csv(file="Log_NSEMTO_sa.csv", sep=",")
NSEMTO_sa<- ts(dat$Log_NSEMTO_sa, start=c(2011,1), frequency=12)
```

```
NSEMTO_sa_asb <- window(NSEMTO_sa, start=c(2013,2), end=c(2018,9))

#(v) load data and create time series object for Kenya's Exchange Rate
dat <- read.csv(file="Log_EXR_KN_sa.csv", sep=",")
EXR_KN_sa<- ts(dat$Log_EXR_KN_sa, start=c(2011,1), frequency=12)
EXR_KN_sa_asb <- window(EXR_KN_sa, start=c(2013,2), end=c(2018,9))

#(vi) load data and create time series object for Kenya's Inflation
dat <- read.csv(file="Inf_KN_sa.csv", sep=",")
Inf_KN_sa<- ts(dat$Inf_KN_sa, start=c(2011,1), frequency=12)
Inf_KN_sa_asb <- window(Inf_KN_sa, start=c(2013,2), end=c(2018,9))

#merge the data set into a dataframe for FPEI Impact on NSE MktCap
KN_DF_sa_asb = cbind(FPEO_KN_sa_asb, NSEMCap_sa_asb, RPSC_KN_sa_asb,
EXR_KN_sa_asb,
                   Inf_KN_sa_asb,NSEMTO_sa_asb)

varnames <- colnames(KN_DF_sa_asb)

#(4b) Impact of Positive Shock to FPEO on NSE Market Capitalisation After Structural Break

#Imposing Restrictions
constr <- c(+1, +4, +5)

set.seed(12345)
#MCMC based on the Uhlig (2005) Rejection Method
fpeo_kn_mod_sa_asb <- uhlig.penalty(Y=KN_DF_sa_asb, nlags=2, draws=800, subdraws=800,
nkeep=1000,
                          KMIN=1, KMAX=12, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs2_sa_asb <- fpeo_kn_mod_sa_asb$IRFS

vl <- c("Outflows","NSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"NSE Market Turnover")

irfplot(irfdraws=irfs2_sa_asb, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                          grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=KN_DF_sa_asb, irfdraws=irfs2_sa_asb, nlags = 2, constant = T, labels = vl, target =
TRUE,
                        type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                        legend = TRUE, maxit = 1000)

##############################################################
                                   #Nigerian Data
              ###########################################
                               #Inflows-Overall Sample
                   #######################################

# load data and create time series object
```

```
#(i) load Nigeria's FPEI data and create time series object
dat <- read.csv(file="Log_FPEI_NG_sa.csv", sep=",")
FPEI_NG_sa <- ts(dat$Log_FPEI_NG_sa, start=c(2013,3), frequency=12)

#(ii) load data and create time series object for NSE Market Capitalisation
dat <- read.csv(file="Log_NGMcap_NG_sa.csv", sep=",")
NSEMCap_sa<- ts(dat$Log_NGMcap_NG_sa, start=c(2013,3), frequency=12)

#(iii) load data and create time series object for Real PSC
dat <- read.csv(file="Log_RPSC_NG_sa.csv", sep=",")
RPSC_NG_sa<- ts(dat$Log_RPSC_NG_sa, start=c(2013,3), frequency=12)

#(iv) load data and create time series object for NSE_Market_Turnover
dat <- read.csv(file="Log_NGMTO_NG_sa.csv", sep=",")
NSEMTO_sa<- ts(dat$Log_NGMTO_NG_sa, start=c(2013,3), frequency=12)

#(v) load data and create time series object for Nigeria_Exchange Rate
dat <- read.csv(file="Log_EXR_NG_sa.csv", sep=",")
EXR_NG_sa<- ts(dat$Log_EXR_NG_sa, start=c(2013,3), frequency=12)

#(vi) load data and create time series object for Nigeria's Headline Inflation
dat <- read.csv(file="Inf_NG.csv", sep=",")
Inf_NG<- ts(dat$Inf_NG, start=c(2013,3), frequency=12)

#merge the data set into a dataframe for FPEI Impact on NgSE MktCap
NG_DB_sa = cbind(FPEI_NG_sa, NSEMCap_sa, RPSC_NG_sa, EXR_NG_sa, Inf_NG,
NSEMTO_sa)

varnames <- colnames(NG_DB_sa)

#(3a) #Impact of Positive FPEI Shock on NgSE Market Capitalisation

#Imposing Restrictions
constr <- c(+1, +2)

set.seed(12345)

#MCMC based on the Uhlig (2005) Penalty Method
fpei_ng_mod_sa <- uhlig.penalty(Y=NG_DB_sa, nlags=1, draws=800, subdraws=800,
nkeep=1000,
                        KMIN=1, KMAX=6, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_kn<- fpei_ng_mod_sa$IRFS

vl <- c("Inflows","NgSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"NgSE Market Turnover")

irfplot(irfdraws=irfs1_kn, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                      grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=NG_DB_sa, irfdraws=irfs1_kn, nlags =1, constant = T, labels = vl, target = TRUE,
                        type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                        legend = TRUE, maxit = 1000)
```

```
#################################################
#Outflows-Overall Sample
##################################################

#(4a)Estimating impact of Positive Shock to Portfolio equity outflows on NgSE Market Cap

#(1) Loading data and create time series object for FPEO_NG
dat <- read.csv(file="Log_FPEO_NG_sa.csv", sep=",")
FPEO_NG_sa <- ts(dat$Log_FPEO_NG_sa, start=c(2013,3), frequency=12)

#merge the data set into a dataframe for FPEO Impact on LuSE MktCap
NG_BD_sa = cbind(FPEO_NG_sa, NSEMCap_sa, RPSC_NG_sa, EXR_NG_sa, Inf_NG,
NSEMTO_sa)

varnames <- colnames(NG_DB_sa)

#Imposing Restrictions
constr <- c(+1, +4)

set.seed(12345)
#MCMC based on the Uhlig (2005) Penalty Method

fpeo_ng_mod_sa <- uhlig.penalty(Y=NG_BD_sa, nlags=1, draws=950, subdraws=950,
nkeep=1000,
                        KMIN=1, KMAX=6, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs1_ng<- fpeo_ng_mod_sa$IRFS

vl <- c("Outflows","NgSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"NgSE Market Turnover")

irfplot(irfdraws=irfs1_ng, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                        grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=NG_BD_sa, irfdraws=irfs1_ng, nlags =1, constant = T, labels = vl, target = TRUE,
                        type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                        legend = TRUE, maxit = 1000)

###############################################
#Outflows-After Structural Break
################################################

#(i) load data and create time series object for Nigeria FPEO After Structural Break
dat <- read.csv(file="Log_FPEO_NG_sa.csv", sep=",")
FPEO_NG_sa <- ts(dat$Log_FPEO_NG_sa, start=c(2013,3), frequency=12)
FPEO_NG_sa_asb <- window(FPEO_NG_sa, start=c(2015,5), end=c(2019,3))

#(ii) load data and create time series object for NgSE Market Cap
dat <- read.csv(file="Log_NGMcap_NG_sa.csv", sep=",")
NSEMCap_NG_sa<- ts(dat$Log_NGMcap_NG_sa, start=c(2013,3), frequency=12)
NSEMCap_NG_sa_asb <- window(NSEMCap_NG_sa, start=c(2015,5), end=c(2019,3))
```

```
#(iii) load data and create time series object for Real Private Sector Credit
dat <- read.csv(file="Log_RPSC_NG_sa.csv", sep=",")
RPSC_NG_sa<- ts(dat$Log_RPSC_NG_sa, start=c(2013,3), frequency=12)
RPSC_NG_sa_asb <- window(RPSC_NG_sa, start=c(2015,5), end=c(2019,3))

#(iv) load data and create time series object for NgSE Market Turnover
dat <- read.csv(file="Log_NGMTO_NG_sa.csv", sep=",")
NSEMTO_sa<- ts(dat$Log_NGMTO_NG_sa, start=c(2013,3), frequency=12)
NSEMTO_NG_sa_asb <- window(NSEMTO_sa, start=c(2015,5), end=c(2019,3))

#(v) load data and create time series object for Nigeria's Exchange Rate
dat <- read.csv(file="Log_EXR_NG_sa.csv", sep=",")
EXR_NG_sa<- ts(dat$Log_EXR_NG_sa, start=c(2013,3), frequency=12)
EXR_NG_sa_asb <- window(EXR_NG_sa, start=c(2015,5), end=c(2019,3))

#(vi) load data and create time series object for Nigeria's Inflation
dat <- read.csv(file="Inf_NG.csv", sep=",")
Inf_NG<- ts(dat$Inf_NG, start=c(2013,3), frequency=12)
Inf_NG_asb <- window(Inf_NG, start=c(2015,5), end=c(2019,3))

#merge the data set into a dataframe for FPEO Impact on NgSE MktCap
NG_DF_sa_asb = cbind(FPEO_NG_sa_asb, NSEMCap_NG_sa_asb, RPSC_NG_sa_asb,
EXR_NG_sa_asb,
                     Inf_NG_asb,NSEMTO_NG_sa_asb)

varnames <- colnames(NG_DF_sa_asb)

#(4b) Impact of Positive Shock to FPEO on NgSE Market Capitalisation After Structural Break

#Imposing Restrictions
constr <- c(+1,+3,+4, +5)

set.seed(12345)
#MCMC based on the Uhlig (2005) Rejection Method
fpeo_ng_mod_sa_asb <- uhlig.penalty(Y=NG_DF_sa_asb, nlags=1, draws=950, subdraws=950,
nkeep=1000,
                        KMIN=1, KMAX=3, constrained=constr, constant=TRUE, steps=24)

#Impulse Responses
irfs2_sa_asb <- fpeo_ng_mod_sa_asb$IRFS

vl <- c("Outflows","NgSE Market Capitalisation","RPSC", "Exchange Rate", "Headline Inflation",
"NgSE Market Turnover")

irfplot(irfdraws=irfs2_sa_asb, type="median", labels=vl, save=TRUE, bands=c(0.16, 0.84),
                        grid=TRUE, bw=FALSE)

#Robust test_Fry and Pagan (2011) MT method
fp.target(Y=NG_DF_sa_asb, irfdraws=irfs2_sa_asb, nlags = 1, constant = T, labels = vl, target =
TRUE,
                       type = "median", bands=c(0.16, 0.84), save=TRUE, grid=TRUE, bw=FALSE,
                       legend = TRUE, maxit = 1000)
```