UNIVERSITY OF ZULULAND

SYSTEMIC RISK, FINANCIAL STABILITY, AND MACROPRUDENTIAL POLICY RESPONSES IN EMERGING AFRICAN ECONOMIES

By

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DECLARATION

I, **Kehinde Damilola ILESANMI** declare that:

This thesis has been completed by myself and that except where otherwise indicated, the research document is entirely my own.

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DEDICATION

This thesis is dedicated to the Almighty God

ABSTRACT

The extent of the damage caused by the 2007/08 global financial crisis (GFC) has forced policymakers all over the world to respond promptly in order to mitigate its effect, a process in which they are still engaged in, particularly in advanced economies. The main objective of this study is to measure systemic risk in African emerging economies and develop a macroprudential regulatory framework to mitigate or limit the effect of such risk. More specifically, the study intends to1) Developing financial stress index (FSI) for the Emerging African economy; 2) Investigate the possibility of Early Warning Signal (EWS) helping in predicting and preventing or minimising the effects of the crisis on financial institutions; 3) Assess the resilience of individual banking companies to adverse macroeconomic and financial market conditions using stress testing technique; 4) Identify the source of fluctuation within the system; 5) Identify and measure systemic risk emanating from the capital flow (surge) as well as its effects on financial stability. This study contributed to the body of knowledge by measuring systemic risk in emerging African economies. To the best of my knowledge, there have not been any studies that have been conducted for the measure of systemic risk with the context of emerging African economies. The target economies include South Africa, Egypt, Nigeria, and Kenya.

The first objective of the study is to construct a financial stress index (FSI) for emerging African economies. The FSI which is aimed at revealing the functionality of the financial system a single aggregate indicator that is constructed to reflect the systemic nature of financial instability and as well to measure the vulnerability of the financial system to both internal and external shocks.

The result shows that both the domestic and international shocks created uncertainty in the economies under consideration. On the international scene, we have the financial crisis while on the domestic scene; we have slow growth, banking crisis, energy crisis, labour crisis, coupled with political uncertainty. The FSI is also useful and appropriate as the dependent variable in an early signal warning model, and as well be used to gauge the effectiveness of government measures to mitigate financial stress. The models forecasting performance was tested using the ordinary least square methods and it affirmed that the model is reliable and that the FSI can be used for prediction of a future crisis.

The aim of the second objective is to develop an early warning signal (EWS) model to predict the possibility of the occurrence of a financial crisis in emerging African countries. The multinomial logit model built by Bussiere and Fratzscher (2006) was adopted to afford policy makers ample time to prevent or mitigate potential financial crisis. In summary, the result suggests that emerging African economies are more likely to face financial crisis as debts continue to rise without a corresponding capacity to withstand capital flow reversal as well as excessive FX risk due to currency exposure. The result further indicates that rising debt exposure increases the probability or likelihood of the economies remaining in a state of crisis. This result confirms the significance of a financial stability framework that fits Africa's emerging economies characteristics such as rising debt profile liquidity and currency risk exposure.

The third objective is to test the resilience of the financial sector using stress testing technique. Macro stress testing is a multi-step simulation process aimed at estimating the impact of credit risk shock on macroeconomic as well as financial sectors. In this study, a two-step approach was employed in this chapter. The first step involves analyzing the determinants of credit risk in 4 Emerging African economies during the period 2006m1 to 2012m12 using the panel Auto Regressive Distribution Lag (ARDL) model. Second, the vector autoregressive (VAR) models were employed to assess the resilience of the financial system as well as the economy to adverse credit risk shocks. The result shows that all the variables under both the macro and financial model jointly determine credit risk, although when examined on an individual basis only, UMP, IBR, and INF have a significant impact on NPL in the long run. For the macro stress testing, the VAR methodology was employed to stress test the emerging African economy financial sector and the result indicated that there a significant relationship between changes in output gap (GAP) and the nonperforming loans. A significant relationship was also established between inflation and nonperforming loans. In all, South Africa and Nigeria's financial system seems more resilient to credit losses associated with this scenario without threatening financial stability compared to Kenya and Egypt.

The fourth objective examined the sources of capital flows surge and their impact on macroeconomic variables. This study employed a $P{-}SVAR$ to investigate the source capital flow surge within the system. The main findings of the result indicate that capital flow, which is proxied by FDI, is influenced by a wide variety of macroeconomic variables such as inflation, export growth and unemployment. There is therefore need for the implementation of capital controls framework tame massive capital inflows. Nevertheless, such a mechanism should not undermine the impact of capital inflows on employment, growth and financial stability.

The fifth objective of the study is aimed at identifying and measuring the sources of systematic risk and its impact on the stability of the financial system using the Conditional Value-at-Risk methodology. The main finding of the study indicates that at the normal and extreme event the banking sector contributes positively and significantly to the real economy for all the countries except for Nigeria at the extreme event or 1 percent quantile. This study, therefore, concludes that the banking sector, stock market volatility contributes greatly to systemic risk in emerging African economies. The individual bank also contributes significantly to systemic risk for all the economies although the magnitudes are relatively different across economies. This finding is of great interest to policymakers since it shows that the banking sectors as well as stock market volatility have a negative impact on the real economy. This result is plausible as the banking and financial sector for most emerging economies constitute a greater proportion of the real economy. There is, therefore, need for a regulatory framework to reduce risk emanating from the banking sector as well as the financial markets.

In summary, due to huge capital flows and rising debt level in emerging African economies, there is, therefore, a need for a macroprudential policy that will fit African economies as well as the implementation of capital controls framework tame massive capital inflows. Efforts should be made to reduce the rising debts profile of most countries and that will require a greater level of commitment from their respective government and central banks. However, these should be in the interest of the growth and stability of the financial system and the real economy at large. In the case of the banking sector, since it has a great impact on triggering systemic risk, more effort should be utilized to continue to monitor its performance so that potential risk can be detected early and nip in the bud.

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LIST OF ACRONYMS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ALSI	All-Share Index
BIS	Bank of International Settlement
BoE	Bank of England
BoJ	Bank of Japan
BU	Bottom-Up
CAR	Capital Adequacy Ratio
CBK	Central Bank of Kenya
CBN	Central Bank of Nigeria
CCAR	Comprehensive Capital Analysis and Review
CDS	Credit Default Swap
CEBS	Committee of European Banking Supervisors
CFSI	Cleveland Financial Stress Index
CISS	Composite Indicator of Systemic Stress
CoVaR	Conditional Value-at-Risk
DCRP	Domestic Credit to Private
DFAST	Dodd-Frank Act
DGDP	Debt to Gross Domestic Ratio

DSGE	Dynamic Stochastic General Equilibrium
DTI	Debt-to-Income
EACMAC	East Africa Community Monetary Affairs Committee
ECM	Error Correction Mechanism
EGY	Egyptian Pounds
EMEs	Emerging Market Economies
ES	Expected Shortfall
EWS	Early Warning Signal
EXR	Exchange Rate
FCI	Financial Condition Index
FDI	Foreign Direct Investment
FIT	Flexible Inflation Targeting
FSAP	Financial Sector Assessment Program
FSI	Financial Stress Index
GARCH	Generalised AutoRegressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
GFC	Global Financial Crisis
ICFA	Implied Cash Flow Analysis
IFS	International Financial Statistics
IRF	Impulse Response Function

IMF	International Monetary Fund
INF	Inflation
INM	Interbank Network Model
IT	Inflation Targeting
KCFSI	Kansas City Financial Stress Index
KYS	Kenyan Shillings
LM	Lagrange Multiplier
LTCM	Long Term Capital Management
LTV	Loan-to-Value
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MES	Marginal Expected Shortfall
MCI	Monetary Condition Index
NGR	Nigerian Naira
NPLs	Nonperforming Loans
OLS	Ordinary Least Square
PSVAR	Panel Structural Vector Autoregression
RMSE	Root Mean Square Error
SARB	South Africa Reserve Bank
SCAP	Supervisory Capital Assessment Program

SIC	Schwarz's Information Criterion
SIFI	Systemically Important Financial Institutions
SSA	Sub-Sahara Africa
TD	Top-Down
TIC	Theils Inequality Coefficient
UMP	Unemployment
USA	United State of America
VAR	Vector Autoregressive
VaR	Value-at-Risk
VEW	Variance Equal Weight
VDC	Variance Decomposition
ZAR	South African Rand

CHAPTER ONE
INTRODUCTION

1.1 BACKGROUND

The magnitude of the damage caused by the 2007/08 global financial crisis (GFC) which was as a result of the loose economic and financial conditions, low inflation, high-risk appetite, inadequate regulation and supervision among others has forced central banks, financial authorities and many other policy institutions throughout the world, to react swiftly in order to mitigate its fallout, a process in which they are still engaged in, particularly in advanced economies (Alberola, Trucharte, and Vega, 2011). The financial nature of the crisis has also strengthened the commitment of the regulatory authorities to improve their surveillance and reinforcement of financial stability (Alberola et al., 2011). At the instance of the GFC, the general perception was that African economies were going to be affected only to a limited extent. This is due to their limited depth and low integration of their financial system with the United States and European capital market (Allen and Giovannetti, 2011). This later changed as events unfolded. African economies became vulnerable to trade linkages and disruption of trade finance that accompanied the global financial crisis (Allen and Giovannetti, 2011). This has indeed revealed Africa's vulnerability to external shocks as well as their low resilience level (Allen and Giovannetti, 2011).

Prior to the GFC, the general policy strategy put in place by central banks for managing economies were the monetary policy and prudential supervision of the financial system (Hahm, Mishkin, Shin and Shin, 2012). According to central banks, traditionally the tasks of financial stability was mostly achieved through financial supervision and regulation (microprudential policy) while price stability was the target of monetary policy. Within this framework, monetary policy contributed to financial stability by attaining an environment of macroeconomic stability. In the aftermath of the crisis, this is not seen as enough, so that there is a growing consensus that monetary policy and financial stability should be more integrated into the overall policy framework within the central banks (Alberola et al., 2011).

Also, the combination of loose monetary and regulatory policies led to excessive credit growth and housing boom in many countries which culminated in the financial stress; this has accelerated the need to go beyond a purely microeconomic approach to financial regulation and supervision (Quint and Rabanal, 2013; Vermandel, 2014). The credit crunch which is seen as the most severe economic contraction in recent times after the Great Depression not only flattened the world economy but probed the policy strategies put in place to manage the economy (Hahm et al., 2012). This has led to a new focus on macro-prudential regulation and supervision, that is, regulation and supervision of the financial system that focuses on system-wide risk, rather than microprudential policy which focused on the riskiness of individual financial institutions, as an important policy tool to promote a healthy economy (Hahm et al., 2012).

According to International Monetary Fund (IMF), Bank of International Settlements (BIS) and the Financial Stability Board (FSB), macroprudential policy (MPP) is defined as those policies used as a prudential toolkit to limit/reduce systemic risk or system-wide financial risk, ensure stability of the financial system as a whole against domestic and external shocks (BIS, 2011; Nier, JÃ¡come, Osinski and Madrid, 2011). The major role of MPP is to identify potential systemic risk, formulate appropriate policy response and ensure proper implementation of the policy response (Vermandel, 2014). In addition to that, macro-prudential policy is also aimed at ensuring stability of the financial system in a global sense by preventing or mitigating systemic risks that emanate from developments within the financial system, taking into account macroeconomic developments, so as to avoid periods of widespread distress (Nier et al., 2011; Vermandel, 2014).

1.2 PROBLEM STATEMENT

Massive growth in balance sheets in the financial system brought about by robust macroeconomic performance (boom) and low-interest rate led to the GFC. Overconfidence in the self-adjusting ability of the financial system led to an underestimation of the consequence(s) of the accumulation of growing stocks of debt and leverage, which resulted from booming credit and asset prices - most notably in the housing sector - and was reflected in historically low levels of asset price volatility and risk premia. The crisis has undermined the widespread conviction that mature economies with sophisticated financial markets are naturally self-equilibrating as well as exposing the limitation of the traditional analytical approach to financial instability (Borio, 2011; Vermandel, 2014). The role of financial innovation and financial deregulation in magnifying the boom and the unwinding of financial imbalances and their consequences on the economy was not taken into consideration (Galati and Moessner, 2012). Furthermore, the consequences (e.g output fall, rise in unemployment) of the 2007 sub-prime crisis in the US exposed the limitations of the economic framework that was successful in providing macroeconomic stability during the "great moderation" (that is the period preceding the crisis which was characterised by an unusually high degree of macroeconomic stability coupled with steady growth as well as low and stable inflation in most advanced economies) period.

The event of the financial crisis has also shown that correlations across assets and banks' balance sheets can sharply increase and pose a systemic risk (Alberola et al., 2011). According to Liao, Sojli, and Tham (2015), systemic risk is endogenously created within the financial system due to exposure of banks to common macroeconomic factors and contagion through interbank linkages. The crisis also revealed that even though individual risks may be forecasted and limited, financial shocks to a single firm can quickly spread across a large number of institutions and markets, thereby threatening the whole system (Kama, Adigun, and Adegbe, 2013; Manizha, 2014). Coupled with the aforementioned scenario is the difficulties in measuring, monitoring and managing the underlying risk, and a structure of incentives that hinder an appropriate behavioural response to changes in risk, even when these are correctly identified (Crockett, 2010; Kama, Adigun and Adegbe, 2013; Manizha, 2014). These scenarios have posed a series of questions to policymakers such as how can systemic risk be quantified and the scope of the effectiveness of prudential controls? Can Early Warning Signal (EWS) help in predicting and preventing or minimising the effects of crises on the financial institution? How can the resilience of the financial sector coping with macroeconomic shocks be assessed? What are the various sources of fluctuations in the system?

Since then, policy agenda has shifted towards a macroprudential approach to bank regulation with the main aim of ensuring the soundness of the financial system through risk assessment and mitigation although researchers and policymakers are faced with the challenge of how to define and measure system-wide risk (Manizha, 2014; Visco, 2011). The idea of MPP is to combat the fallacy of composition: "if each individual bank is sound, the whole banking system must be sound" (Alberola et al., 2011). Therefore, the microprudential approach to supervision which focuses on ensuring safety and soundness of the individual financial institution needs to be complemented with a macro-prudential approach as it turned out to be inadequate in containing system-wide risks (Alberola et al., 2011; Filiz Unsal, 2013). Hence, a different approach to ensuring system-wide stability needs to be implemented.

Another challenge faced by policymakers in the debate over the implementation of macroprudential policy is whether it should be independent or set by the central banks in line with monetary policy decisions to ensure financial stability (Alberola et al., 2011; Vermandel, 2014). While there is a high level of awareness of the contribution of monetary policy to financial stability, its role is in practice limited (Alberola et al., 2011). A loose monetary policy may amplify the financial cycle or, conversely, a macroprudential policy that is too restrictive may have detrimental effects on credit provision and hence on monetary policy transmission. Where low policy rates are consistent with low inflation, they may still contribute to excessive credit growth and to the build-up of asset bubbles and induce financial instability (Vermandel, 2014).

According to Vermandel (2014), "the main argument in favour of mixing both monetary and macroprudential policies is the following: to the extent that macroprudential policy reduces systemic risks and creates buffers, it helps the task of monetary policy in the face of adverse financial shocks while the argument against lie in its potential conflict of interest, or at least trade-offs, between the two policies". This study tends to contribute to the existing literature on whether the macroprudential policy should be independent or mixed with Monetary Policy in African emerging economies. Despite the fact that macroprudential is directed at strengthening the resilience of institutions to shocks, containing the accumulation of risk as well as to ensure financial stability, its objectives are not clearly defined and quantifiable as those of monetary and fiscal policy (Kama, Adigun, and Adegbe, 2013; Visco, 2011).

Furthermore, it is worthy of note that most low-income countries in Sub-Sahara Africa on average have been resilient to the effect of the global financial crisis due to their improved regulatory framework and supervision, structural reforms, sound macroeconomic policies (Caggiano, Calice, Leonida, Kayizzi-mugerwa, and John, 2013; IMF, 2012). However, increased financial deepening and financial transaction are likely to make the banking system more vulnerable (Caggiano et al., 2013). In this respect, early warning signals (EWSs) can be a valuable tool for regulators to identify and mitigate such risk that may arise. In spite of the above, emerging economies have received no specific attention in the context of building EWSs. From the foregoing and the historical experience, it is clear that macroeconomic stability is not a sufficient condition for ensuring financial stability. For example, before the GFC started, financial imbalances built up in advanced economies despite stable growth and low inflation. The microprudential regulation and supervision, which geared towards ensuring the health and safety of individual financial institutions, turned out to be inadequate as system-wide risks could not be contained. Therefore, a different/broader approach to mitigate the system-wide risk based on macro-prudential supervision is needed (Filiz Unsal, 2013).

There is a need for emerging markets to limit domestic financial vulnerabilities which results from weaker growth, lower commodity prices, and a stronger dollar while strengthening their resilience to the changing global environment (IMF, 2015). Also according to Bhattacharya (2009), since financial sectors are vulnerable to instability and systemic risk, monitoring these sectors as well as the spillover effects of the weaknesses in the real sector is of great importance based on the severity and frequency of financial crises. An adequate design of macro-prudential policy could address effectively the financial stability objectives and, through its interaction with the monetary policy and microprudential policies could adapt better goals and instruments in the central banks' policy framework.

1.3 OVERVIEW OF THE FINANCIAL SECTOR AND FINANCIAL STABILITY

The strong relationship between financial stability and economic growth was confirmed by the global financial crisis. Prior to the emergence of the crisis, policymakers assumed that the financial system was strong, based on large balance sheet position, yet there was a gradual build-up of large vulnerabilities that were overlooked by financial regulators and supervisors of individual financial institutions (IMF, 2011). Also, the complex nature of the financial system made it difficult for regulators to predict the extent of exposure and potential risk spillovers. This is because of the high level of interconnectedness among firms, high risk in both the funding and liquidity market, growth of the shadow banking sector, which engaged in financial intermediation through banks structured investment vehicle (SIV) and most importantly there was a lack of an effective regulatory framework to ensure the stability of the entire financial system (IMF, 2011). These practically made them not to be proactive until the crisis could not be averted.

Since then, the global economy has been in a state of fragility. For example, in the periods of high uncertainty and excessive volatility, investors often become more risk-averse towards certain asset classes due to uncertainty in the value of the asset (SARB, 2017b). As a result, institutions become cautious about their investment decisions which will, in turn, make households to cut spending. This will most likely lead to a slowdown in economic activities, thereby bringing a negative feedback loop between the financial system and the real economy (SARB, 2017a).

The stability of the financial system is affected by slow growth through unemployment and reduced ability of households and corporate firms to service their debts with financial institutions (SARB, 2017a). This has bolstered the need to monitor the trends in the financial system in order to detect possible systemic spillovers that could hamper the stability of the entire financial system and the economy.

During the GFC, the world's top 15 banks experienced a downturn in their market capitalisation from about US$1. 7 trillion in 2007Q2 to about US$500 billion in 2009Q1 (Wim, 2009). Also, asset values worth US$25 trillion were wiped out of the global market within one year-an amount equivalent to the gross domestic product of the US and European Union combined (Wim, 2009). There was also a significant cut in consumer demand as a result of loss in personal wealth coupled with the loss of jobs-about 3.1 million Americans lost their jobs in 2008 alone (BLS[1], 2009). Although most emerging economies were resilient to the impact of the crisis, many of the advanced economies are still trying to find lasting solutions to the problems created by the GFC, especially in the banking sector (Volz, 2012). The are some lessons learnt from the GFC and they are: 1) The negative impact of a disruption in the financial system on economic activities could be worse than anticipated; 2) price and output stability which is the major aim of monetary policy is not sufficient to guarantee financial and by extension economic stability, and

[1] Bureau of Labor Statistics, United States Department of Labor

3) the huge cost of cleaning up the crisis due to its impacts on growth (slowing down growth) and deteriorating budgetary position of government.

In response to the financial crisis, central bank authorities in major advanced countries lowered their interest rate to a historically low level coupled with pursuing an unconventional monetary expansion policy such as large asset-buying programs. This low-interest rate regime in advanced economies such as United State, Europe and Japan has consequently led to a rising debt level of firms in emerging market economies, especially in the construction as well as the oil and gas sectors (IMF 2015). The rise in firms' debt-to-asset ratio, commonly known as leverage, has often included a higher share of foreign-currency liabilities. Although, incurring leverage can be beneficial since it can facilitate investment and thereby faster growth; however, it can be a source of risks as investors in advanced economies often resort to high return investments such as commodity (IMF 2015). These commodity prices have become relatively more important in the rise in corporate debts in emerging markets. Corporate debts in emerging African economies have been on the increase in recent years. The corporate debt-to-GDP ratio major African countries as shown in Figure 1.1 indicated a persistent increase since 2010, but with notable differences across countries.

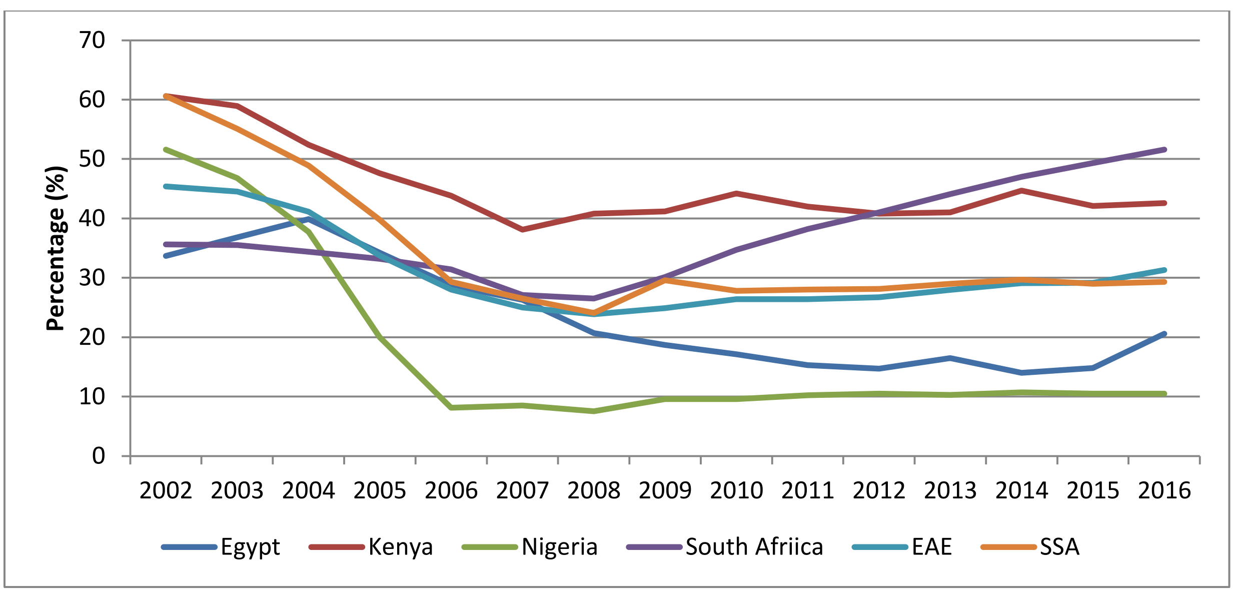

Figure 1. 1: Gross Debt to GDP in Emerging African Economies

Source: World Bank (2017)

It is noteworthy also that the emerging market debt composition has also changed during this period. Specifically, bank loans still account for the largest share of corporate debt, while the share of bonds has nearly doubled over the last decade, reaching 17 percent in 2014 (IMF 2015). Therefore, according to Gaston Gelos, Chief of the Global Financial Stability Analysis Division at the IMF "the dependence of Emerging African economies on favourable global financial conditions makes them vulnerable to rise in interest rate, dollar appreciation and global risk aversion" (IMF, 2015).

Emerging African markets could serve as a source of risk to the global financial system through their high levels of indebtedness in the non-financial corporate sector, which is around 100 percent of GDP 2016 compared to just 60 percent of GDP in 2001 (SARB, 2017a). This non-financial corporate sector can be vulnerable to the rising global interest rate when combined with a slowdown in both global and domestic growth and depreciation of the domestic currency. Although the extent to which it impacts depends on the nature of hedging done by corporate entities and the terms of such loans (SARB, 2017a).

Furthermore, the rise in debt-service cost due to rising interest rate, also, local currency depreciation associated with rising policy rates in the advanced economies would make it increasingly difficult for emerging market firms to service their foreign currency-denominated debts if they are not hedged adequately (IMF 2015). It will also negatively affect profitability and spilling over to the domestic banking sector through a decline in corporate deposits and/or increase in corporate defaults (SARB, 2017a). At the same time, lower commodity prices reduce the natural hedge of firms involved in this business (IMF, 2015).

1.3.1 Systemic Risk in Emerging African Markets

Systemic risk is the risk of disruptions to the financial system which is mainly as a result of impairment in all parts of the financial system (IMF, 2011) with the potential of exacting a negative impact on the real economy. Systemic risk occurs when there is a high financial exposure. For example, the 1987 stock market bubble in the United States, the Long-Term Capital Management (LTCM) crisis in 1998 which were fuelled by high leverage and financial exposure generated systemic risk (IMF, 2011).

Financial stability awareness, and financial stability analysis and monitoring have been in existence even before the global financial crisis started in 2007. What has changed is the focus of financial stability administrators or supervisors. The GFC revealed the lapses in the way and manner we understand and analyse the financial system. This also includes the data and toolkit used in measuring financial system vulnerabilities as well as the policy tools used to mitigate potential threats to the financial system (Berner, 2014).

These lapses not only contributed to the crisis but also hampered efforts to mitigate/contain it.

Although significant progress has been made so far with respect to financial stability, these include 1). Identifying financial system vulnerabilities which are caused by increased leverage, excessive liquidity and maturity transformation, interconnectedness, and complexity, 2). Developing a new toolkit for monitoring the financial system, and 3). financial reforms which have strengthened most bank's balance sheets through new capital and liquidity requirements. This usually serves as buffers against loss and hurdles for risk-taking (Berner, 2014). However, much work still needs to be done in terms of addressing the gaps in analysis, data, policy toolkit and regulatory arbitrage. It must be of note that regulatory arbitrage and financial innovation are promoting the migration of financial activity toward the shadow banking sector (Berner, 2014).

In the past two decades, emerging economies have become more closely integrated with the seemingly unstable global financial system. Due to this integration, the traditional cross-border linkages have deepened and the external balance sheet has expanded rapidly. Also, the external influence of the global financial system on the domestic credit, equity and property markets within the emerging economies have increased tremendously (Akyuz, 2015). This has created several cross-border transmission channels of financial shocks. This implies that most of these countries are now vulnerable to external financial shock irrespective of their foreign reserve, the balance of payment, and external debts (Akyuz, 2015). Also, due to the fact that banking systems of emerging economies have deepened and developed substantially, it is now able to provide the credit needed for the economy to expand, and the shadow banking sector is growing at a comparable pace on the side, one cannot really say that vulnerabilities are exclusively building up from external imbalances or global factors (Lepers and Serrano, 2017). Hence, a study of financial stability in emerging economies should be holistic enough to take care of every source of vulnerability and not just focus on external capital flows (Lepers and Serrano, 2017).

Furthermore, capital flows surge to emerging African countries is a major source of threat/risk to the macroeconomic and financial stability with the region (Filiz Unsal, 2013). Portfolio inflows to emerging market economies are on track to reach $285 billion in 2017 (Lee, 2017). This was as a result of bleak growth prospects in advanced countries. The monetary expansion in Europe and the United States (US) caused Brazil's president Dilma Rousseff in March 2012 to voice her concerns about the resulting "monetary tsunami" that was making its way to emerging economies (Volz, 2012; Belke and Volz, 2015). It must also be noted that any disruption or misalignment in the functioning of the financial sector due to excessive exposure to risk and financial deleveraging are major constraints to economic growth. Although the increase in the inflow of capital from the advanced countries drives growth, on one hand, it also spreads risk on the other hand. This will lead to a reduction in income, increased income inequality, increased unemployment level, loss of confidence in the system and social unrest (Buncic and Melecky, 2013).

In most emerging African economies, there has been more focus on the management of capital inflow surge. This is because of its importance and global financial integration for economic growth and risk sharing. Capital flows to emerging African economies have been on the increase since after the GFC in 2008 and reaching its peak in 2013, after which there was a decline up till 2015. However, it has been on the increase since 2016 (Figure 1.3). This gradual increase in capital inflows is risks to macroeconomic and financial stability, hence the need for a macroprudential to address these risks.

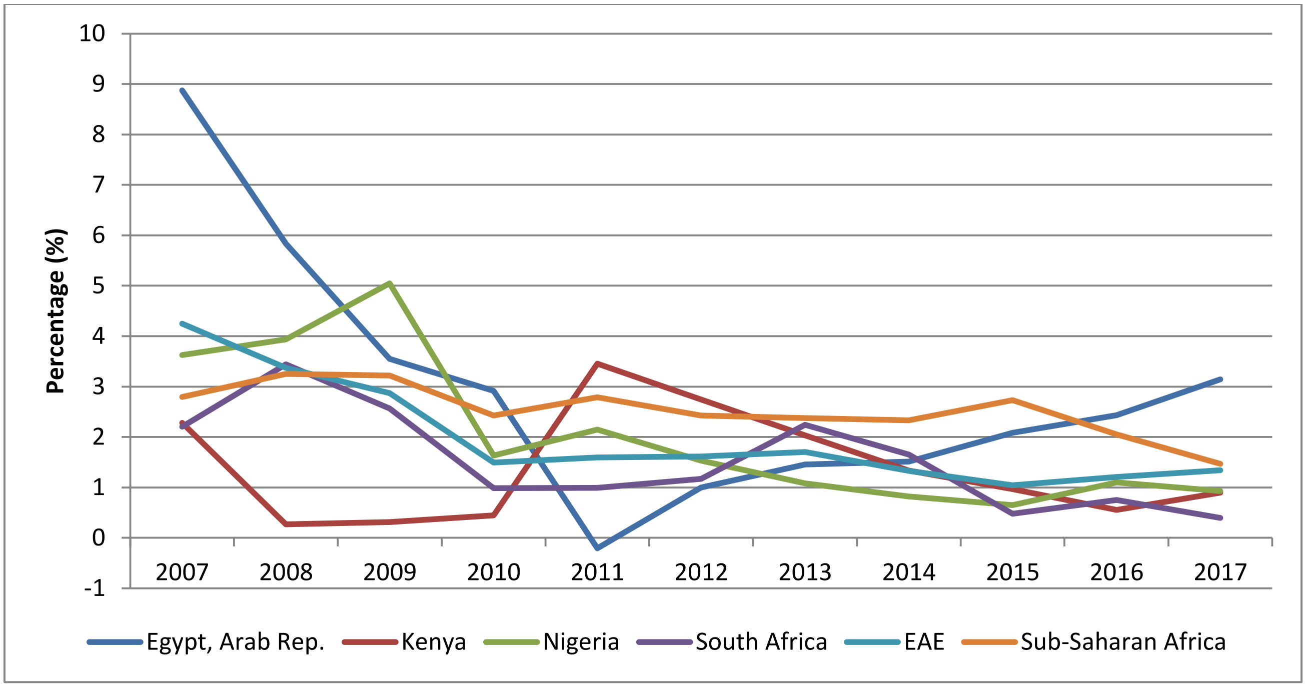

Figure 1. 2: Net Capital Inflow to Emerging Economies

Source: World Bank (2019)

To address these risks, policymakers have turned their attention to the use of macroprudential measures, in addition to monetary policy. Macroprudential policies are aimed at addressing issues regarding the financial system with respect to the real economy. The issues include preventing systemic risk which reduces the probability of systemic events relating to the financial institutions, markets, and instruments that can negatively affect the stability of the entire financial sector.

1.4 NEED FOR THE STUDY

The high level of interdependence and interconnectedness of the modern global financial system and concerns by monetary authorities on the potential systemic effect of financial crisis on economies have raised the need for the development of a better macroprudential framework for the management of systemic risk and supervision of the financial system at the macro level (Patro, Qi, and Sun, 2013). Also, the fact that the financial sector has been a major contributor to the growth and stability of various economies has necessitated the need for the development of several financial stability initiatives to mitigate any crisis that might arise from the sector (SARB, 2016).

Firstly, the cost of such crisis could be so severe in terms of loss in reserve, the decline in output, rising unemployment, and poverty (Bhattacharyay, 2009). In addition, the intensity and the speed with which shocks spread within the entire financial system highlights the need to identify, measure and understand the nature and the source of systemic risk in order to improve the underlying risks that banks face, to avert banks' liquidation ex ante and to promote macro-prudential policy tools (Huang, Zhou, and Zhu, 2012).

Secondly, the rapid resumption of huge capital inflows into the African economies from the advanced countries increase the vulnerability of the financial system thereby posing risks to macroeconomic and financial stability (Filiz Unsal, 2013). Although the increase in the inflow of capital from the advanced countries drives growth, on one hand, it also spreads risk on the other hand. It must also be noted that any disruption or misalignment in the functioning of the financial sector due to excessive exposure to risk and financial deleveraging are major constraints to economic growth. This will lead to a reduction in income, increased income inequality, increased unemployment level, loss of confidence in the system and social unrest (Buncic and Melecky, 2013).

Thirdly, the GFC also revealed that there is still a lot to be done to better understand the sources of systemic risk and as well as how such risks associated with financial decisions should be controlled so as to dampen out fluctuations (Bernanke, 2011; Vermandel, 2014; Li and Zinna, 2015). While the conventional monetary policy prevents capital flows from exacerbating overheating pressures and consequent inflation, it is not sufficient to guard against the risk of financial instability (Filiz Unsal, 2013). Policy makers are now faced with the challenge of not only understanding and determining the reforms needed for the financial system, but also the regulatory structures and policy instruments needed to enhance financial stability. There have also been calls by monetary authorities and other stakeholders in the financial sector for the adoption of policies that will aid better management of systemic risk (Patro et al., 2013). However, before such policies can be adopted, it is essential to understand systemic risk and how it can be measured and monitored (Patro et al., 2013).

The fourth need for the study is the possibility of predicting accurately the timing of the crisis. It is important to be fully prepared for the crisis if it can't be prevented and to detect the crises early in order to minimize their impact and limit their damaging effects (Bhattacharyay, 2009). To the best of my knowledge, there have not been any studies that have been conducted on emerging African economies trying to measure systemic risk. This study intends to contribute to most recent efforts of predicting risks associated with the financial system in emerging African economies through an early warning signal (EWS) model as well as quantifying systemic risk using the conditional Value-at-Risk (CoVaR) model. While previous studies have focused on advanced economies (Barrel et al., 2010; Babecky et al., 2014) and low-income countries (Caggiano, Calice, and Leonida, 2014) there is no known study that has examined it in the context of emerging African economies. The most common measure of risk used by financial institutions is the value at risk (VaR). The VaR focuses on the risk of an individual financial institution (Adrian and Brunnermeier, 2011). However, individual institution risk may not necessarily reflect the risk inherent in the entire financial system. This study employs the $CoVaR$ model developed by Adrian and Brunnermeier (2011) to measure systemic risk. The $CoVaR$ model is useful in studying risk spillover as well as capturing systemic risk through the VaR of an institution conditional on other institutions in distress (Drakos and Kouretas, 2015).

The target economies include South Africa, Egypt, Nigeria, and Kenya. These target economies are drawn from the list of the countries with the ```largest economies as well as stock market development. The study used various macroeconomic and financial data such as real GDP, inflation; stock market returns etc. and they were sourced from the Countries' central banks databases, Bankscope and Bloomberg database. The study will cover a period between 1980 and 2017 although subject to the availability of data from the various sources.

1.5 RESEARCH QUESTIONS

Based on our review of the existing literature, and the need to assess the health and vulnerability of financial institutions to potential risks, the following research questions that would be particularly useful to address the design and implementation of macro-prudential policy instruments are identified. The main question that arises is what can be done to reduce the damage of these events (systemic risk).

1. How can the financial stress index (FSI) for the Emerging African economy be developed?
2. Can Early Warning Signal (EWS) help in predicting and preventing or minimising the effects of crises on financial institutions?
3. What are the determinants of credit risk and how can the resilience of the financial sector coping with macroeconomic shocks be assessed?
4. What are the various sources of fluctuations in the system?
5. How can systemic risk be quantified and what is the scope of the effectiveness of prudential controls of systemic risk?

1.6 OBJECTIVES

The general objective of the macroprudential policy is to limit the cost or effect of financial distress to the economy. Alternatively, it can be described as limiting the likelihood of failure and the corresponding cost of the financial system. These effects include those that arise from any moral hazard induced by the policies pursued. The main objective of this study is to measure systemic risk in African emerging economies and develop a macroprudential regulatory framework to mitigate or limit the effect of such risk. More specifically, the study intends to

1. Developing financial stress index (FSI) for the Emerging African economy
2. Investigate the possibility of Early Warning Signal (EWS) helping in predicting and preventing or minimising the effects of the crisis on financial institutions.
3. Assess the resilience of individual banking companies to adverse macroeconomic and financial market conditions using stress testing technique.
4. Identify the source of fluctuation within the system.
5. Identify and measure systemic risk emanating from the capital flow (surge) as well as its effects on financial stability.

1.7 CONTRIBUTION TO THE BODY OF KNOWLEDGE

The ultimate objective of every national government is to create a sustainable level of economic growth and stability of the entire system through the various sectors of the economy such as the financial sector, industrial sector, agricultural sectors as well as the service sector. The financial sector has been a major contributor to achieving the objective. The central bank is the regulatory authority saddled with the responsibility of ensuring the soundness and stability of the financial sector. However, the primary focus of most central banks over the years has been on ensuring price stability. But the financial crisis has brought about policy rethink as not just to pursue price stability but also ensure the stability of the entire financial system.

The focus of central banks has been on assessing risks to system-wide stability and development of macro-prudential policy instruments to mitigate the effects of macroeconomic shocks in the system. This study intends to develop policy measures that will assist the regulatory authorities in this respect. Financial stability index will also be developed for the emerging African economies.

This study contributes to most recent efforts of predicting risks associated with the financial system in emerging African economies through an early warning signal (EWS) model as well as quantifying systemic risk using the conditional Value-at-Risk (CoVaR) model. This is because most of the previous studies have focused more on advanced and low-income economies. According to Van den Berg et al. (2008), EWS model built by aggregating countries on regional basis outperforms one where all countries are pooled together which will improve the model's ability to predict the crisis. Therefore, measuring systemic risk within the emerging African market using a single model will be of great benefit to central banks and other regulatory authorities within the African region. This is because it is important to be able to quantify the risk that poses a threat not only to a particular economy but also the regional financial system.

This study will employ a panel structural vector autoregression (PSVAR) to identify sources of fluctuations, answer questions about structural changes, forecast and predict the effect of policy changes within the emerging markets. This study will also employ the stress testing technique to assess the resilience of the financial sector to macroeconomic shocks in the system. This technique will help in evaluating the vulnerability of the system against major shock.

1.8 STRUCTURE OF THE THESIS

This study is structured into eight chapters. Introduction and background of the study were presented in chapter 1, while a conceptual review was presented in chapter 2. The first objective of the study, which is to develop a financial stability index for emerging African economies is presented in Chapter 3. EWS model approach to predicting the emergence of systemic risk is presented in Chapter 4. Chapter 5 and 6 are devoted the third (Identify and measure systemic risk emanating from the capital flow (surge) as well as its effects on financial stability) and fourth (Identify the source of fluctuation within the system.) objectives respectively. The fifth object which is aimed at performing stress test for banks in emerging African economies is presented in Chapter 7. Finally, the summary of the main findings, conclusion and policy implications are presented in Chapter 8.

1.9: SPECIFIC TERMINOLOGIES USED

Microprudential Policy: Microprudential policy is an approach to supervision focuses on ensuring the safety and soundness of the individual financial institution. Under this approach, the risk in the market depends on individual institution's decision and the sources of such risk are independent of the collective impact of the interaction between individual institutions.

Macroprudential Policy: Macroprudential policy is an approach to supervision that is aimed at limiting the build-up of financial risk within the system. The goal of macroprudential policy is to ensure a viable financial system as a whole in terms of avoiding macroeconomic cost or disruptions emanating from the instability of the financial system, strengthening the resilience of the financial system to shocks and economic imbalances and as well limiting the spread of the international financial crisis.

Financial Stability: Financial stability can be defined as a financial system that is resilient to financial shock, facilitates efficient financial intermediation and mitigates the macroeconomic costs of financial disruption in order to maintain confidence in the system. In other words, it entails the smooth functioning of a complex nexus of relationships among financial markets and institutions operating within the given legal, fiscal and accounting framework.

Global Financial Crisis (GFC): The Global Financial Crisis (GFC) is referred to as the period of extreme stress within the global financial market and banking system between mid-2007 and early 2009, leading to large losses and huge bailout cost to the government.

Procyclicality: Procyclicality refers to the tendency of financial variables to fluctuate around a trend during the economic cycle

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CHAPTER TWO

SYSTEMIC RISK AND FINANCIAL STABILITY: A CONCEPTUAL REVIEW

This chapter gives a brief account of the conceptual review on systemic risk and financial stability. The study focuses on the Emerging African economies and they are drawn from the list of the countries with the largest economies as well as the level of stock market development. as per the S&P Dow Jones Indices Country Classifications, 2014. As per the S7P Dow Jones Indices, Nigeria was grouped among frontiers economy, although they have all the quality for being grouped as one of the emerging African economies. This chapter is divided into eight main sections. Section one is devoted to discussing some basic concepts on systemic risk and financial stability such as microprudential policy and macroprudential policy. Section 2 gives a detailed discussion on the policy framework for achieving economic stability as it relates to systemic risk and financial stability objective. Financial stability and macroeconomic development which includes the banking sector reforms for emerging African economies are given in Section 3. Section 4 focuses theoretical and empirical review of systemic risk while Sections 5, 6 and 7 are devoted to discussing issues on early warning signal model, financial stress index and stress testing. A chapter summary is given in Section 8.

2.1 A COMPARISON BETWEEN MICROPRUDENTIAL POLICY AND MACROPRUDENTIAL POLICY

Before GFC, financial stability was essentially well-thought-out from a microprudential perspective (Altunbas, Binici and Gambacorta, 2018). The major focus of regulatory policy was to limit the likelihood that individual institutions would fail (microprudential policy), without considering their spill-over effect on the entire financial system and economy as a whole. However, the fall of the Lehman Brothers emphasized the fact that financial stability has a systemic element that cannot be disregarded (Claessens, et al. 2010; Buckley, et al. 2018).

The severity and duration of the downturn triggered by the GFC have brought to the fore the absence of a dependable macro-based financial regulatory framework. As an outcome, addressing the linkage between the financial system stability and economic performance has become a core obligation of regulators, policymakers and researchers (Kahou and Lehar, 2017;

Adrian, 2017). Since then, many countries have implemented macroprudential tools as a method of protecting the financial system.

This is because monitoring risks of each individual financial institutions or considering the financial system as a sum total of its part without taking into consideration, the interconnectedness of these financial institutions is insufficient for financial stability analysis (Smets, 2014; Altunbas, Binici and Gambacorta, 2018). These connections come in different ways ranging from counterparty exposures, exposures to common assets, as well as funding relations. This often obviously lead to seeing the financial system as a network and analyzing the stability of this network (Allen and Gale 2000). In other words, financial stability is seen more from a macroprudential policy perspective which follows a systematic approach in analyzing financial stability (Smets, 2014).

2.1.1 Microprudential Policy

Microprudential policy approach to supervision focuses on ensuring safety and soundness of the individual financial institution (Alberola et al., 2011; Filiz Unsal, 2013). Microprudential coordination assumes that market risk is not dependent on the individual financial institution's decisions and that the sources of risk are exogenous and independent of the collective impact of the interactions between individual institutions (Gadanecz and Jayaram, 2015). That is to say, each institution is treated on a stand-alone basis regardless of its impact on the entire financial system as a whole. One of the aims of microprudential policy is to ensure the financial stability of individual financial institutions. Although microprudential policy focuses on the individual institutions, it was supposed to contribute to the overall soundness of the system as a whole.

The health of the individual financial institutions is a necessary condition for a sound financial system although it is not sufficient due to the complexities of the financial system (Osinski, Seal and Hoogduin, 2013). This is because some actions which are suitable at the individual firm level may be inimical to the entire system due to the structure and interaction within the financial market of which they are part (Alberola et al., 2011; Filiz Unsal, 2013; Osinski, Seal and Hoogduin, 2013). Basically, the microprudential framework suffers what is called "*fallacy of composition*" (Crockett, 2000; Brunnermeier et al., 2009). Borio (2011a) maintains that one of the fundamental rationalities of the microprudential thinking is that "financial stability is ensured as long as each and every institution is sound". The microprudential policy approach to supervision is based on the provisions of the Basle I and II agreements which imposed minimum capital requirements on the banks as a measure of prevention against unexpected losses. Within this framework, the Basel II agreement led to the development of internal systems for measuring market risk and such regulation looked at the soundness of individual financial institutions. Furthermore, a number of these regulatory measures (adequate disclosure and capital requirements, liquidity requirements, prompt corrective action, careful monitoring of an institution's risk-management procedures, close supervision of financial institutions to enforce compliance with regulations, and sufficient resources and accountability for supervisors among others) which were primarily designed to fix market failures are basically the typical features of a well-functioning prudential regulatory and supervisory system (Shin, 2015). However, such regulation focused mainly on the safety and soundness of individual firms, while ignoring factors such as size, the degree of leverage, and interrelationships with the rest of the system. These other factors are catered for by macroprudential policies. Accordingly, Stein (2010) argued that the main goal of financial reform should not just be based on strengthening a few large institutions, but rather to reduce the vulnerability of the entire system of credit creation. In view of these limitations, policies that ensure a system-wide resilience and soundness such as the macroprudential policy should be used to complement the microprudential policy.

2.1.2 Macroprudential Policy

The word "macroprudential" although has become popularized the GFC, it can be traced to the 70s when the major concerns of financial regulation were how to check the rapid growth of loans to developing countries and its possible impacts on financial stability. In addressing this issue, in 1979, the term "macroprudential" was introduced during the Cooke Committee (which later came to be known as the Basel Committee on Bank Supervision) meeting (Kahou and Lehar, 2017).

The 2007/08 GFC has sparked an intense debate on a generally accepted definition of macroprudential policy together with its objectives and instrument, although none has been widely accepted (Brockmeijer et al., 2011). According to the IMF (2011), "macroprudential policy is a complement to microprudential policy for safeguarding the financial stability".

Broadly speaking, macroprudential policy is aimed at ensuring financial stability. It is majorly seen as prudential tools set up with a macro lens to limit systemic risk (system-wide financial risk) (Brockmeijer et al., 2011). According to Suh (2014), a macroprudential policy can be defined as the set of regulatory instruments imposed on financial institutions in order to limit the build-up of financial risk (Suh, 2014). The aim of macroprudential policy is to ensure a viable financial system as a whole in terms of avoiding macroeconomic cost or disruptions emanating from the instability of the financial system, strengthening the resilience of the financial system to shocks and economic imbalances and as well limiting the spread of international financial crisis (Tomuleasa, 2015). It is seen as a complement to monetary policy. Macroprudential coordination regards the sum total of the risk as an endogenous variable which is contingent on the collective behaviour of the financial institutions within the system. This is clearly evident in events that characterized the GFC. According to Gourinchas and Obstfeld (2012), Geanakoplos (2010), and Schularick and Taylor (2012), this period was characterized by domestic credit expansion as well as an appreciation of the real currency. During the period, it is intelligent for individual financial institutions to raise their leverage and as well provide cheap credit; however, if all these institutions make such decision simultaneously, the end result will be an accumulation of financial imbalances and therefore lay the foundation for a financial crisis (Brunnermeier et al., 2011).

Also, times of recession are always characterized by a limited supply of liquidity in the financial sector. In such instances, it is rational to force a distressed financial institution to dispose of some of its assets to provide liquidity and shrink the risk in its portfolio. Nevertheless, if a substantial percentage of the financial institutions dispose-off their assets simultaneously, a fire sale[2] arises and a large shift in the supply curve of these assets leads to a drastic drop in the price of those assets. The fall of prices may damage solvent institutions holding those assets and create a cascade of fire sales. Fire sales aggravate the fragility of the financial sector if they occur on a large scale.

[2] A fire sale is essentially a forced sale of an asset at a price below the market rate. This might be due to a number of reasons. For detailed discussions on fire sales see Shleifer and Vishny (2011).

The characteristics of macroprudential policy are its coordination with monetary policy to achieve financial stability as well as other monetary policy targets such as inflation and output gap stability (Suh, 2014). Several studies have been carried out on the macroprudential policy. Some are briefly discussed in this section.

Bahaj and Foulis (2016) who examined macroprudential policy under uncertainty scenario found that the presence of unquantifiable sources of risk, potential asymmetries in policy objectives, ability to learn from policy actions and private sector uncertainty over policy objectives can all lead to more active policies in the face of uncertainty. In their study, Quint and Rabanal (2013) examined the optimal mix of monetary and macroprudential policies using a dynamic stochastic general equilibrium (DSGE) model for the euro area. The model includes real, nominal and financial frictions, and hence both monetary and macroprudential policy can play a role. Their findings revealed that the introduction of a macroprudential rule is helpful in reducing macroeconomic volatility, improve welfare, and partially substitute for the lack of national monetary policies.

Hahm et al. (2012) in their study using Korea as an example examined macroprudential policies in open emerging economies. The study also highlighted how the financial crisis brought about the introduction of MPP to assist in managing the economy and the need for policymakers to monitor the financial cycle and systemic risks. It also discusses one particularly promising measure of the state of the financial cycle, the growth of non-core liabilities of the financial sector, and evaluates macroprudential policy frameworks. Although progress has been made so far by the financial regulators with regards to the functioning of the financial system and especially in the banking sector resilience and supervision, there still remain vulnerabilities outside the banking sector (Berner, 2015). There is, therefore, need to develop tools to address these vulnerabilities.

In the case of advanced and emerging economies, Altunbas, Binici and Gambacorta (2018) analyzed information from 3177 banks over the period 1990–2012 have a significant effect on bank risk and that the responses to variations in macroprudential tools vary between banks, subject on their specific balance sheet features. It was also revealed that macroprudential policies are more effective in a tightening than an easing cycle.

2.1.3 A Comparison between Microprudential and Macroprudential Policies

The fact that both micro- and macroprudential policies are aimed at limiting risk suggest that their goals are typically aligned, although, in practice, this is not the case as they may not be perfectly aligned (Osinski et al., 2013). According to Beyer et al (2017: 10), “the focus of microprudential policy is to contribute to the safety and soundness of individual entities and thereby contribute to the stability of the system as a whole”, while macroprudential policy, on the other hand, encompasses the entire financial system in order to limit the likelihoods of system-wide failure and limit/avoid substantial losses to the economy. This implies that macroprudential policy framework would concurrently look at the “cross-sectional[3]” as well as the “time-dimension” aspects of systemic risks in the financial system, while microprudential policy framework focuses only on the time dimension of risk (Borio and Drehmann 2009; Altunbas, Binici and Gambacorta, 2018). A detailed comparison between microprudential and macroprudential policies is presented in Figure 2.1.

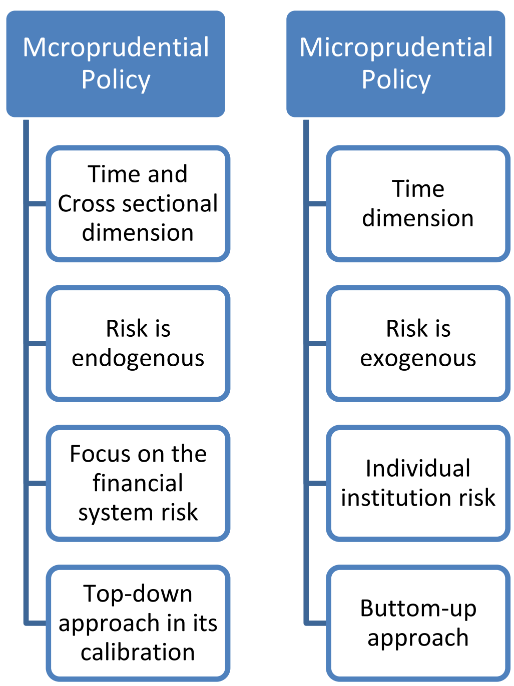


Figure 2. 1: Comparison Microprudential and Macroprudential Policies

[3] Cross-section dimension focuses on the concentration of risks in the financial system and in the systemically important institutions while time dimension measures the risk builds up over time in a financial cycle (See Borio and Drehmann, 2009).

Microprudential policy framework is concerned about limiting the possibility of individual financial institutions from failing and also protecting consumers not minding the systemic effect on the other institutions within the system and by extension the whole economy. Furthermore, the macroprudential dimension views risk as endogenous since institutions can collectively affect economic transactions, while the microprudential dimension views risk as exogenous since individual institutions will generally have little impact on the economy.

While macroprudential buffers are intended to diminish procyclicality, micro requirements are expected to be maintained at all times (Landau, 2009). This may lead to situations where some conflicts arise between the macro and the micro perspective (Schou-Zibell, Albert, and Song, 2010). For example, in terms of liquidity requirements, during financial distress circumstances, a microprudential framework's resolve on sustaining higher liquidity buffers might lead to fire sales of less liquid assets in illiquid markets, however, from the macroprudential policy point of view, it could lead to loss of confidence that could affect other markets (Gadanecz and Jayaram 2015). There is, therefore, need for proper coordination and communication between the microprudential policy and macroprudential policy framework in order to ensure a stable financial system and by extension the whole economy (Economic Stability). Discussion on economic stability is presented in the next section.

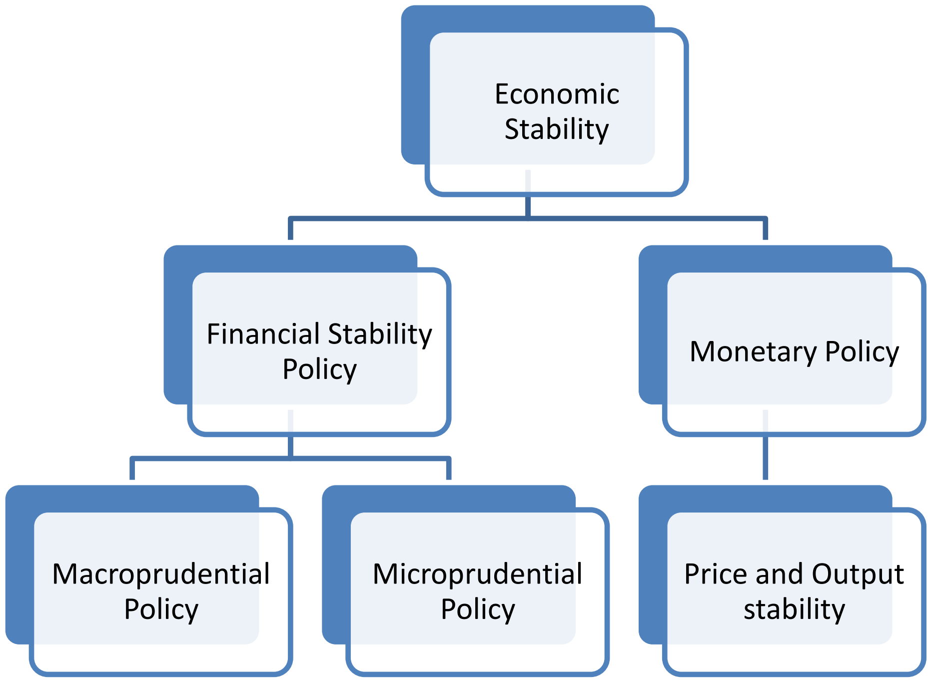
2.2 ECONOMIC STABILITY

The GFC has stressed the negative impacts of macroeconomic instability on the financial system as well as the real economy. Fluctuations in economic activities, rising inflation, growing unemployment, increasing and unsustainable debts levels and high volatility of the exchange rate all have a negative impact on the health and stability of the financial system and the real economy. Maintaining macroeconomic stability is thus is a precondition for a stable financial system. The GFC motivated a good number of central banks to implement explicit[4] financial stability objectives or to adjust the existing arrangement. This often serves as a proactive

[4] Explicit financial stability mandate implies that the central bank has by law be been mandated to take financial stability as its core mandate.

measure against systemic risk (Caruana, 2014). An inventory into the laws and statutes of 144 central banks shows that 82 percent of the regulators adopt explicit financial stability objectives (Jeanneau, 2014; Kim, and Mehrotra, 2017).

An unmistakable message from the GFC is that financial stability has a systemic or macroprudential element that cannot be overlooked. Regarding the financial system as just the sum of the different aspects drives one to disregard the system's propensity to swing from boom to bust (Caruana, 2014; Smets, 2014). It is noteworthy that in the build-up to the GFC, it was the advanced economies that ignored systemic dimension compared to the emerging economies who are more aware of the importance of considering the entire financial system as a whole and more ready to intervene whenever there is a build-up of imbalances that appeared to be conflicting with economic fundamentals (Caruana, 2014). Despite the fact that most central banks are aware of the extent to which the economy could be negatively affected by the financial disruption, nevertheless, their (central banks') general equilibrium modelling framework did not incorporate financial frictions as a major source of business cycle fluctuations (Adrian, 2017). This, however, stimulated literature that now incorporate financial stability objectives and macroprudential policies into macro models with monetary policy (Kima and Mehrotrab, 2017).
Figure 2.2 provides a framework for achieving economic stability. Accordingly, it is the combination of financial stability policy and monetary policy that guarantees the achievement of economic stability.



Source: Author

Figure 2. 2: A Schematic Framework of Economic Stability

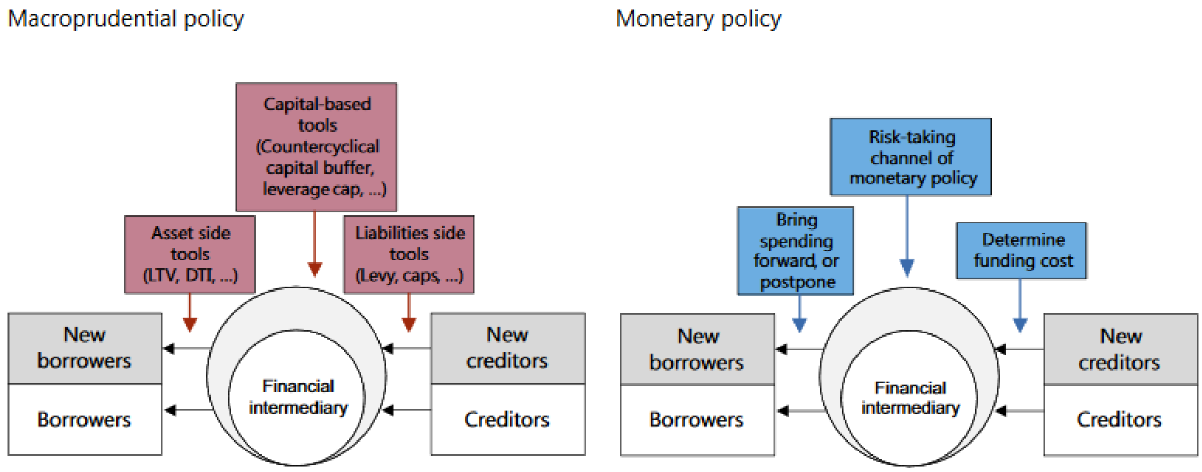
The monetary policy objective is achieved through price and output stability while financial stability objective is achieved using the microprudential and macroprudential policy frameworks. Although, as noted earlier, the microprudential policy framework focuses on the stability of individual financial institution while the macroprudential policy framework focuses on the stability of the entire financial system and by extension achieving economic stability (See Figure 2.2).

2.2.1 A Comparison between Monetary Policy and Macroprudential Policy

In the fallout of the GFC, there has been a strong argument about the responsibility of the central banks and monetary policy, considering, especially the impact of inflation target administrations and the strength of banking supervision on financial system stability (Tabak, et al. 2016). Inflation targeting was believed to have undermined financial stability due to its focus on two macroeconomic variables such as price and output (Kuttner, 2013). There are divergent views on the interaction between macroprudential policy and monetary policy (Gadanecz and Jayaram, 2015). On one hand, it is argued that macroprudential policy might be used as a complete substitute for monetary policy in terms of stabilizing the economy, as long as the transmission channels are similar (Cecchetti and Kohler, 2012). This strands of literature opined that there exists a dichotomy between monetary policy and financial stability policy in which these two types of policies would be conducted independently (Adrian, 2017). In their view, the aim of monetary policy instruments is to curtail inflation and output gaps, while financial stability is aimed at preventing or limiting excessive risk-taking and safeguarding the entire system.

On the other hand, while most central banks maintained this stance (dichotomy between monetary policy and financial stability policy), there are contrary views that monetary policy and financial stability are essentially interconnected and that the supposed dichotomy is a false one (Gadanecz and Jayaram 2015; Shin, 2015; Mourmouras, 2016). They argued that macroprudential tools cannot be a complete replacement for monetary policy (Stein, 2013). This is because policy rates are the general price of leverage which applies to all agents in the economy and presents virtually no scope for regulatory arbitrage (Gadanecz and Jayaram 2015). Financial stability can be influenced by monetary policy, while macroprudential policy which is aimed at promoting financial stability will have an influence on monetary policy (Mourmouras, 2016).

An essential question begging for answer is to ascertain whether monetary policy and macro-prudential policies are complements or substitutes? Must they be pulled in the same direction or opposite directions? More recent studies stressed the connections between monetary and macroprudential policies. According to Shin (2015) and BIS (2015), both the monetary and macroprudential policies influence both the demand for and supply of credits by influencing consumers or firms to either borrow more or less and as well as the funding choices on financial institutions respectively (See Figure 2.2).



Source: Shin (2015)

Figure 2. 3: A Comparison between Monetary Policy and Macroprudential Policy

According to Bruno et al. (2016) and Angelini et al. (2014), there is a positive correlation between monetary and macro-prudential tools in the Asia-Pacific region and in the context of large financial shocks respectively. Also, in the study conducted by Bailliu et al. (2015), it was revealed that in the case of a deviation in credit growth, the combination of both monetary and macroprudential policies interact to restore financial balance in the system. As noted earlier, one of the major aims of macroprudential policy is to limit the level of procyclicality of the financial system. This aim is achieved by influencing the financial intermediation process which operates on the assets, liabilities and leverage of intermediaries (Shin, 2015). In order words, monetary policy should address financial stability issues, particularly with regard to responding to potential asset price bubbles. For example, in the speech delivered by Professor John Iannis Mourmouras, Deputy Governor of the Bank of Greece, on monetary policy and financial stability, he stated that "*If macroprudential policies are implemented to restrain a credit bubble, growth of aggregate demand will be slowed down due the slowing down in credit growth. In order to offset the slow growth in aggregate demand, there would be a need for an easier monetary policy to stabilize inflation and output. Otherwise, if policy rates are kept low to stimulate the economy, there is a greater risk that a credit bubble might occur. This may result in tighter macroprudential policies to ensure that a credit bubble does not get started. Coordination of monetary and macroprudential policies would make it easier to pursue all three objectives of price stability, output stability and financial stability*" (Mourmouras, 2016). In this respect, central banks cannot take the view that there is a dichotomy between monetary policy and macroprudential policy. Nonetheless, there still exist critical contrasts between monetary policy and macroprudential policy. The major contrast is that macroprudential policy approach focuses on specific sector or practices while monetary policy influences risk-taking more broadly, both within the domestic financial system and also across borders, and this is difficult to avoid (Shin, 2015).

2.2.2 Policy Strategy before the GFC

Prior to the 2007/08 GFC, the general consensus among central banks and academia for a policy framework for price stability is a form of flexible inflation targeting, while supporting a contrast between monetary policy and financial stability policy. A growing number of central banks, both in developed and emerging economies, had embraced a combination of inflation targeting regime and exchange rate flexibility regimes. On the other hand, small, integrated economies had the alternative of for all intents and purposes relinquishing the exercise of monetary policy by fixing their exchange rates.

There was increased confidence in the effectiveness of this method to ensure macroeconomic stability. The correlation between inflation targeting and macroeconomic stability made stakeholders and regulators believe that financial stability objectives should be individually or exclusively approached using the microprudential regulatory and supervisory measures. Monetary policy would be used to take care of inflationary tendencies, flexible exchange rate would guarantee an even balance of payment, while microprudential regulation and supervision, would, in turn, forestall excessive risk-taking by banks (Borio, 2011; Svensson, 2016). However, the approach had been devastated by the magnitude and synchronization of the asset price booms and busts which resulted in the GFC. This shows that there is interdependence between macroeconomic stability and financial stability and that there is a need for a coordinated approach (between monetary policy and macroprudential regulation) in response to the crisis (Borio, 2011; Agenor and Pereira da Silva, 2012). A brief note on inflation targeting and flexible inflation targeting are given in the next subsection.

2.2.2.1 Inflation Targeting (IT)

Inflation targeting is a framework that involves setting a numerical objective for the inflation rate (Kuttner, 2013). The main point of inflation targeting is the minimization of a loss function that involves output volatility and the squared deviation of inflation from its target.

$$L = E_t \sum_{i=1}^{\infty} \delta^i \left[(\pi_{t+1} - \bar{\pi})^2 + \vartheta(y_{t+1} - y^*)^2\right]$$

where y is the log of real gross domestic product (RGDP), y^* is the potential output, π is the inflation rate, while $\bar{\pi}$ is the inflation target. δ is the discount factor, and ϑ is the weight attached to the output volatility relative to the deviation of the inflation rate from its target. The end point of the target is to ensuring a balance between the marginal cost of deviation of inflation from its target and the marginal cost of a nonzero output gap (Kuttner, 2013).

As of 2008, the IMF classified 31 central banks as inflation targeters. The US Federal Reserve and Swiss national bank although are not inflation targeters, they adopt a monetary policy that is closely related to inflation targeting. Under the inflation targeting framework, there is no reference to or provision for ensuring financial stability. This made, until recently, the objective of financial stability and its legal basis a vague for most central banks. The emergence of the GFC led to a suggestion that the inflation targeting framework should be modified to include explicit financial stability objective (Kuttner, 2013).

2.2.2.2 Flexible Inflation Targeting (FIT)

The simple monetary policy framework adopted by virtually all regulatory authorities (central banks) not pursuing exchange rate peg included a solid, trustworthy, responsible commitment to ensuring that the inflation rate is stable in the long run, as well as reducing output volatility in the short run (Kuttner, 2013). This is known in the academic literature as "flexible inflation targeting" (Svensson, 1997, 2016). The adoption of a flexible inflation targeting framework is aimed at limiting not only the variability of inflation but also of the output gap as well as the real exchange rate (Svensson, 2000). In other words, flexible inflation targeting is aimed at reducing the deviations of inflation from its target rate (Kuttner, 2013). While some central banks adopt an explicit numerical inflation objective (Reserve Bank of South Africa, Reserve Bank of New Zealand among others) which are grouped as a full-fledged inflation targeters, others are, hesitant or unwilling to be so explicit (which is referred as "gradualism" according to the Federal Reserve) in which the policy interest rate is believed to display a considerable level of inactiveness (Mishkin, 2010a).

The rationale for the implementation of the FIT framework is based on some principles which are also known as the neoclassical synthesis (Goodfriend and King, 1997). These principles, according to Mishkin (2011a) "are: 1) inflation is always and everywhere a monetary phenomenon; 2) price stability has important benefits; 3) there is no long-run trade-off between unemployment and inflation; 4) expectations play a crucial role in the determination of inflation and in the transmission of monetary policy to the macroeconomy; 5) real interest rates need to rise with higher inflation, i.e., the Taylor Principle; 6) monetary policy is subject to the time inconsistency problem; 7) central bank independence helps improve the efficiency of monetary policy; 8) commitment to a strong nominal anchor is central to producing good monetary policy outcomes; and 9) financial frictions play an important role in business cycles".

In spite of these obvious contrasts in communication strategy/technique, the essential approach of central banks with an independent monetary policy before the crisis was fundamentally the same. They were ready to conduct monetary policy under a solid duty to stabilize inflation in the long run. According to Svensson (2002), most central bank that shows that it will seek after the standard target of minimizing inflation and the output gap in an intertemporal setting is seen as a flexible inflation targeter. Prior to the financial crisis, most central banks who adopts an independent monetary policy fell into this group.

2.2.3 Policy Strategy after the GFC

Prior to the 1970s, the financial sector had been stable. However, since then, the occurrence of banking crises has rapidly increased (Hildebrand, 2007). From that point forward, most economies have encountered extreme cases of banking crises (Hildebrand, 2007). Prominent among such crisis include Japan and the Scandinavian banking crisis in the early 1990s, the Asian flu, as well as the recent global financial crisis (GFC) of 2007/2008.

2.2.2.1 Flexible Inflation Targeting (FIT)

The main key point is that the lessons from the crisis did not undermine the advantages of having a solid and credible commitment to stabilize inflation in the long run, which is the major reason for the adoption of FIT (Mishkin, 2011, 2014). This commitment to ensuring long-run stabilization of inflation can be more useful during the period of financial stress when the appropriate expansionary monetary policy is required, however, this will depend on the expectations that inflation remains grounded (Mishkin, 2008). Nevertheless, while the case for a flexible inflation targeting framework is not weakened by the lessons from the GFC, they do propose that specifics of how such a framework is implemented would profit from some rethinking. The main discussion in this regards is the thinking about the lean versus the clean debate. This debate is basically on whether monetary policy should react to asset-price bubbles.

1) The Lean Versus Clean Debate of Asset-Price Bubbles

According to Mishkin (2010), not all asset price bubbles are alike. There are basically two types of asset-price bubbles which will be discussed here with respect to the lean versus clean debate (Figure 2.3). They are the credit-driven bubble and irrational exuberance bubble.

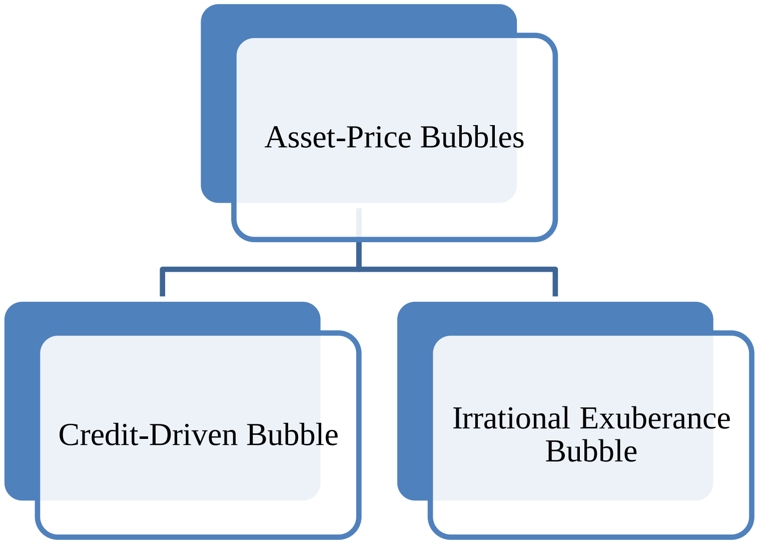


Figure 2. 4: Types of Asset-Price Bubbles

a) Credit-driven bubble

Asset price bubbles in itself do not cause financial instability, financial instability only occurs when asset price bubbles interact with the financial sector-this is referred to as credit-driven bubbles and believed to be very harmful to the system (Mishkin, 2011). This, in turn, leads to a chain of events starting with a credit boom which is as a result of exuberant expectation about economic prospects. The end result is a surge in demand for some assets, thus, raising their prices, which, in turn, boosts further lending against these assets, increasing demand, and hence their prices, even more (Mishkin, 2011, 2014). This feedback loop can generate a bubble, and the bubble can cause credit standards to ease as lenders become less concerned about the ability of the borrowers to repay loans and instead rely on further appreciation of the asset to shield themselves from losses (Mishkin, 2014).

Sooner or later, the bubble bursts. The fall in asset prices at that point prompts a reversal of the feedback loop in which loans turn sour, lenders cut back the supply of credit, the demand for assets falls further, and price drops much more. The subsequent loan losses and fall in asset prices erode the balance sheets at financial institutions, further diminishing credit and investment across a broad range of assets. The decline of lending dampens business and household spending, which weakens economic activity and increases macroeconomic risk in credit markets. Ultimately, the interaction between asset prices and the health of financial institutions subsequent to the collapse of an asset price bubble can threaten the entire financial system (Mishkin, 2014).

b) Irrational exuberance bubble

The irrational exuberance bubble is less harmful to the financial system compared to the credit-driven bubble. This type of bubble is caused by optimistic expectation. A good example is the technological shock of the late 1990s which was only followed by a mild recession compared to the crisis that followed the credit-driven bubbles such as the GFC (Mishkin, 2011). The technological shock was not propagated by a feedback loop between bank lending and rising equity, therefore, the bursting of the bubble was not followed by deterioration in the bank balance sheet as in the case of credit-driven bubbles (Mishkin, 2014).

Nevertheless, the major lesson from the recent GFC is that a credit-driven bubble burst can be very costly and as well difficult to clean up. Also, such kind of bubble can still occur even if price and output stability is achieved during the period leading up to them. In reality, price and output stability might essentially propel credit-driven bubbles because it can blindfold market participant and make them underrate the level of risk within the economy (Mishkin, 2010). The case for leaning against potential bubbles rather than cleaning up afterwards has, therefore, become much stronger (Mishkin, 2014). This is due to the high cost of cleaning up as such crisis is usually followed by a sharp rise in government indebtedness arising from the bailout of financial institutions, fiscal stimulus packages, a sharp contraction in the economy, reduction in tax revenue among others (Reinhart and Rogoff, 2009; White, 2009).

2.2.2.2 Inflation Targeting and Financial Stability

Prior to the 2007/08 global financial crisis (GFC), the general consensus among central banks and academia for a policy framework for price stability is a form of flexible inflation targeting, while supposing a contrast between monetary policy and financial stability policy. There was no consensus as to how the regulatory authority to respond to the crisis. The GFC motivated a good number of central banks to implement explicit financial stability objectives or to adjust the existing arrangement. This, however, raised the possibility of trade-offs between price and financial stability objectives. While some (Blanchard et al. 2010; Cukierman, 2013) scholars pointed out that inflation target policies may have been the cause of financial instability due to the fact that regulatory authorities have relegated financial stability issue to the background by ignoring changes that occurred in the banking system such as the occurrence of asset price bubbles, others (Fazio et al. 2015; Svensson, 2009) are of the view that the crisis has little to do with the monetary policy but market failures because most systemically important banks were more stable under inflation targeting regime.

Ensuring that the major variables that are linked to financial stability such as asset price and credit growth are stable is believed to impact positively on financial stability, inflation and output stability (Borio and Lowe, 2002). Although, in existing studies, it is not clear if adopting inflation targeting alone or in combination with output stabilization will ensure financial stability in the normal course of monetary policymaking (Cecchetti et al., 2000; Bordo and Jeanne, 2002;

Roubini, 2006; Posen, 2006). The line of thought in this regards is that stable inflation is beneficial to consistent and efficient flow funds amongst banks and borrowers since undue real wealth transfer between them due to inflation or deflation can be to a great extent evaded or circumvented. Likewise, prices can more likely guide consumption and investment and consequently help dodge over-investment and conceivable failures to service accrued debt.

When inflation is stable, deflationary pressure, which often leads to distress selling of asset to pay off debts is checkmated (Mishkin, 2005). Also, ensuring that output is stable, debt servicing capacity of borrowers can be enhanced, and this, would, in turn, reduce the possibility of liquidation. In any case, it has been contended that monetary policy may not be able to promptly address possible future economic instability implied by unrestrained credit growth and asset prices by simply concentrating on prices and/or output (Cecchetti et al., 2000; Bordo and Jeanne, 2002; Borio and Lowe, 2002). Also, inflation and output stabilization is unlikely to be sufficient in inducing stable growth in asset price and credit, and thereby a stable financial sector. Accordingly, monetary policy can become more effective in reaching its macroeconomic objectives, including financial stability, by stabilizing asset prices and/or credit, in addition to inflation and output.

2.3 FINANCIAL STABILITY

Financial stability can be defined as the probability that a shock in the financial system would limit its ability or capacity to its core function of providing credit to the economy (Adrian, 2017). Financial stability though not an end in itself is a precondition for sustainable economic growth and employment creation (SARB, 2016). It refers to a financial system that is resilient to financial shock, facilitates efficient financial intermediation and mitigates the macroeconomic costs of financial disruption in order to maintain confidence in the system (SARB, 2016; Adrian, 2017). In a broader sense, it encompasses the smooth functioning of a complex nexus of relationships among financial markets and institutions operating within the given legal, fiscal and accounting framework (Gadanecz and Jayaram, 2008).

According to the definition given by the European Central Bank (ECB, 2007), financial stability can be likened to as a condition in which the financial system which comprises of the financial intermediaries, market, and market infrastructure is capable of being resilient against shocks and unravelling financial imbalances, thereby mitigating the tendency of disruption in the financial intermediation process which can significantly obstruct the allocation of savings to profitable investment opportunities.

The GFC, which resulted in a substantial cost to the global economy including rising government debt, increasing unemployment, resulted in a policy shift from the monetary policy which is aimed at ensuring price stability to the macroprudential policy which focuses on ensuring financial stability (Cunningham and Friedrich, 2016). This led to a global comprehensive reform agenda to ensure that the financial system is more resilient to withstand shocks and reduce the risk of future crisis (Cunningham and Friedrich, 2016). A financial stability shock induces a fall in asset prices which deteriorates the balance sheets of economic agents as well as their net worth (Blot, Creel, Hubert, Labondance, & Saraceno, 2015).

This will reduce agents' desire to borrow which in turn leads to a reduction in investment. This scenario leads to a decline in economic activity and prices (Blot et al., 2015). The financial crisis has led policymakers to refocus their efforts to ensure the stability of the financial system. Based on this premise, central banks have been quite active in supporting financial stability in a variety of ways, such as publicly sharing their assessments of financial system vulnerabilities and risks and helping to strengthen regulation, supervision and macroprudential measures (Cunningham and Friedrich, 2016). However, the use of monetary policy instruments for managing financial stability risks is more widely debated because central banks may face a trade-off between attaining their inflation targets in a timely manner and exacerbating financial stability risks. Recent research suggests that central banks that tend to have stronger financial stability mandates and less influence over regulatory and macroprudential tools are more likely to use monetary policy to address financial stability risks (Cunningham and Friedrich, 2016).

2.3.1 Macroeconomic Developments and Financial System Stability in Africa

In recent years, African economies have witnessed a surge in capital flows which was mainly driven up by both the easy global monetary conditions as well as its own enhanced macroeconomic performance (Caruana, 2014). Monetary policy has been instrumental in ensuring macroeconomic stability in Africa despite several domestic instabilities and external shocks, which include high financial volatility that these economies are being confronted with

(Lynn Ng and Vergara, 2017). As banks in advanced economies shed assets and risks, a greater share of cross-border bank flows into Africa has come from banks domiciled in major emerging market economies (EMEs) such as Brazil, China and India.

The continent, which has always been seen as the most economically under-developed region of the world, has witnessed improved growth over the year (Allen, Otchere, Senbet, 2011). According to the World Development Indicators (World Bank, 2018), the 2009 GDP per capita for the Sub-Sahara Africa (SSA) rose from $1515.687 to $1647.818 in 2016 and this represents an 8.7 percent growth for the period (WDI, 2018). Growth in the Sub-Sahara African (SSA) region is seen to have recovered to 2.4 percent in 2017, after decelerating sharply to 1.3 percent in 2016, due to the recovery of commodity prices (Kambou, 2018). This recovery in the region's economy can be attributed to the recovery in the region's largest economies such as Nigeria, Angola and South Africa. For example, in Nigeria, the reduction in militant attack on oil pipelines was instrumental to the recovery of the oil sector and helped the country come back to the path of growth, as output grew by 0.8 percent in 2017 (from -1.6 percent in 2016), although activities in the non-oil industrial sector remained weak due to insufficient power generation (IMF, 2017; World Bank, 2018).

In the case of South Africa, bumper crop harvest due to increased rainfalls and increased mining activities helped the economy recover (from 0.59 percent in 2016 to 1.27 percent in 2017), although growth in other sectors was subdued due to heightened elevated policy uncertainty, which continued to weigh on business confidence (World bank, 2018). For Angola, a perplexing operational environment restricted investment in the oil sector. Kenya's economy has been on a positive trend and recent data suggests that the economy is still on course for a Q3 2018 following a strong performance in the Q2 2018 data released. Although the growth rate fell to 4.9 percent in 2017 from 5.87 in 2016, the estimate is hovering around 5.5 percent as at the end of Q2 2018 (World Bank, 2018; Bouzanis, 2018). The rebounding of the economy of SSA is expected to continue, sustained mainly by rise in commodity prices, stable oil prices etc. as it is expected that the region's growth will rise from 2.8 percent in 2017 to 3.2 in 2018 (this year), rising further to 3.8 percent in 2019 (Biuzanis, 2018).

The continent has also witnessed an increase in the spread of pan-African banking groups[5], which has encouraged innovation, competition and better service delivery through improved functioning of the interbank and foreign exchange markets (Caruana, 2014). The banking system in Africa comprises of the Central Banks and commercial banks. Although the Central Banks are constitutionally independent of government control, they still work closely with the ministries of finance of their countries and in most cases, the central bank governors and other key members are appointed by the head of government of the country.

The deposit-taking institutions comprise of both local and foreign bank subsidiaries. Foreign banks have played an important role in banking development in Africa; their share of total African banking has increased significantly (Biuzanis, 2018). This can be credited to the financial sector transformations embarked upon by these countries, which in turn have led to the opening up of the markets in Africa and the attendant entry of foreign banks (Biuzanis, 2018).
However, these gains come with its' own financial stability risk. The interconnectedness of the operations of these banks poses a great deal of risk to the host country. These among other challenges call for an improved regulatory and supervisory framework in order to gauge the health of the financial system and as well deal with potential risks that may arise.

2.3.1.1 Banking Sector Reforms in Emerging African Economies

African economies have undergone a series of banking sector reforms over the years. These reforms include restructuring and privatization of state-owned banks, recapitalization and other measures that will ensure the development of the banking sector. A brief account of such reforms for emerging African economies such as South Africa, Nigeria, Kenya and Egypt are discussed as follows.

1) South Africa

The South African banking sector is highly concentrated with four largest banks accounting for over 80 percent of the country's total bank assets. Over the years, banking sector reforms which started in the 1990s has produced a relatively sound, efficient and profitable banking sector as

[5] Banks domiciled in Africa with subsidiaries in several other African countries

well as reducing the number of banks from 58 in 2003 to 34 in 2009. This was one of the reasons the sector was able to scale through the period of the GFC without being severely affected. At the moment, the South African banking sector comprises 10 locally controlled banks, 7 foreign-controlled banks, 3 mutual banks, 2 co-operative banks and about 50 branches and representatives of foreign banks with combined total assets of approximately R 6 trillion (Relbank, 2018).

As part of the effort to ensure the resilience of the financial sector to systemic risk, the Financial Sector Regulation Bill was approved by Parliament in June 2017. The bill makes provision for an expanded mandate of the SARB, which includes financial stability. The major aim of financial stability policy is to improve resilience to systemic shocks as well as to lessen the macroeconomic costs of disruption in financial sectors (Groepe, 2017). It is seen as a precondition for sustainable economic growth. The purpose of ensuring financial stability is not just about preventing shocks or crises, but more about identifying and mitigating the build-up of risks and vulnerabilities in the financial sector (Groepe, 2017).

2) Nigeria

In the run-up to the GFC, some factors were found to have led to the 2008 banking crisis in Nigeria. They include macroeconomic instability which was as a result of huge and sudden capital inflows, failures in corporate governance at banks, lack of transparency and information asymmetry on the true financial position of banks, regulatory arbitrage among others (Sanusi, 2012). All these contributed to the failure of the banking system and by extension almost collapsed the entire financial sector. However, in 2004, the banking reform started and it was aimed at strengthening the banking system. Banks were consolidated through merger and acquisitions, thereby raising the capital base of banks from N2 billion to a minimum of N25 billion, which led to the reduction of banks from 89 to 25 in 2005 and then later to 24 (Sanusi, 2012). Other reforms include: Zero tolerance in regulatory framework in data/information rendition/reporting and infractions; Strict enforcement of corporate governance principles in banking; Expeditious process for rendition of returns by banks and other financial institutions through e-FASS; Revision and updating of relevant laws for effective corporate governance and ensuring greater transparency and accountability in the implementation of banking laws and regulations; and the introduction of a flexible interest rate based framework that made the monetary policy rate the operating target and offset inflationary pressures (Sanusi, 2012).

3) Kenya

During the 1980s and 1990s, the Kenyan banking sector experienced major crises due to undercapitalization, weakness in corporate governance and high level of non-performing loans- these led to the failure of a good number of commercial banks, although, non-bank financial institutions were mostly hit (Nyasha, and Odhiambo, 2012). Since then, there has been a number of reforms put in place by the government in order to safeguard and improve the performance of the banking sector. As a result, there has been a shift in the ownership structure of banks from that of state-owned to the private commercial banks as well as improvement in the central bank's oversight function and enforcement of the bank's capital adequacy requirement (Nyasha, and Odhiambo, 2012). The improved performance of the banking sector management structure goes along with the write-off of non-performing loans and cut-back of state interference in the commercial sector (Biuzanis, 2018). The country's banking sector which is made up of about 40 commercial banks is one of the most developed banking systems in Africa (Nyasha, and Odhiambo, 2012). However, there are still challenges within the system. For example, the banking structure is still uneven, with the presence of few large banks in the midst of few small banks that serve niche markets, and do not contribute to competition in the sector (Beck, et al. 2010).

4) Egypt

The Egyptians banking sector was predominantly owned by the state in the 1990s and this made it be uncompetitive (Poshakwale, and Qian, (2011). The sector was characterized by lack of innovation and proper governance structure which led to a huge pile of non-performing loans as well as poor asset quality (Central Bank of Egypt, 2008). However, the banking sector reforms which started in 1990 sought to break the state monopoly (Poshakwale, and Qian, (2011). By 1996, the government amended the banking and credit law that removed the 49 per cent ceiling on foreign ownership of Egyptian banks. In the third and most current phase of reforms starting from 2002, the government launched the Financial Sector Reform Programme with an aim to divest public sector ownership of banks, consolidation of smaller banks and restructuring of state-owned banks (Poshakwale, and Qian, (2011). Between 2005 and 2007, 14 Egyptian banks including some state-owned banks, have been either taken over or merged with foreign banks and this has helped in reducing the level of non-performing loans in Egyptian banks (Poshakwale, and Qian, (2011). According to the recent IMF report, the Egyptian banking sector is liquid, profitable, and well capitalized. The aggregate capital adequacy ratio improved from 14 percent in December 2016 to 15.2 percent in December 2017, while the leverage ratio improved from 4.8 to 6 percent during the same period (IMF, 2018). The nonperforming loan (NPL) ratio improved from 6 to 4.9 percent due to NPL write-offs (IMF, 2018).

2.4 SYSTEMIC RISK:

Systemic risk is an integral element in the design and implementation of macroprudential policy. Basically, systemic risk is the possibility of the occurrence of some events resulting in the obstruction of the financial sector's ability to provide credit in the economy (Yellen, 2010). It is the risk of disruption to financial services which is caused by an impairment of all part of the financial system with the possibility of having severe adverse consequences on the real economy (Brockmeijer et al., 2011; Foggitt et al., 2017). Such events are capable of creating anxiety within the system thereby leading to failure of the financial institution and ultimately collapse of the whole system. However, whether financial failures are sources of systemic risk or not is contingent on the performance or influence of the rest of the financial system on the economy.

This means that the disruption of the financial sector is not only the source of systemic risk but it can be a major factor For example, the 1987 stock market bubble (fuelled by leverage trades) in the United States led to systemic risk, while, on the other hand, the dot.com bubble did not lead to any systemic risk due to limited systemic exposure (Brockmeijer et al., 2011). Similarly, the 1998 Long Term Capital Management (LTCM) crisis is an example of an event bearing systemic risk, while the fall of Amaranth Advisors in 2006 has not brought the threat of significant impairment of the financial system (Brockmeijer et al., 2011). Not all identified credit boom has been a source of systemic risk (Brockmeijer et al., 2011). The systemic risk theoretical and empirical review is discussed in subsection 2.4.1 and 2.4.2 respectively.

2.4.1 Systemic Risk: A Theoretical Framework

According to Liao et al., (2015), systemic risk is created endogenously within the financial system due to the bank's common exposures to macroeconomic factors and contagion through interbank linkage. Prior to the financial crisis, prudential measures only were designed mainly to address individual's banks specific risk, but this does not cater for the negative impact of a bank's default on the other institutions within the system (Liao et al., 2015).

Although, there is no unique or holistic model to measure how moral hazard and adverse selection affects the whole market. Several structural frameworks have been employed to studying systemic risk among which we have the Network theory, Value at risk (VaR), Expected Shortfall (ES), distress insurance premium (DIP), Conditional Value at Risk (CoVaR) (Martinez-Jaramillo et al. 2014; Kanno, 2015). The major weakness of applying the different model in the analysis of systemic risk is that it makes it difficult to make a valid comparison of the different results obtained for the numerous studies (Martinez-Jaramillo et al. 2014).

2.4.1.1 Network Theory (NT)

After the landmark seminar paper delivered by Allen and Gale (2000), network models have been present in the context of financial contagion and systemic risk. However, the topology of real interbank exposures networks is different from the topologies suggested in their paper. For example, Wells (2002) studies the UK interbank exposures network in the context of systemic risk; Boss et al. (2004) provide some empirical data on the interbank exposures network of the Austrian banking system; in Iori et al. (2008), the authors provide some empirical evidence on the topological properties of the Italian Money Market.

The network theory methodology (graph model) is increasingly being used in the field of economics and finance and is very important and prevalent in study of systemic risk based on recent publication especially in the field of financial stability (e.g Martinez-Jaramillo et al. 2014; Nagurney, 2003; Allen and Babus, 2009; Embree and Roberts, 2009; Chapman and Zhang, 2010; Bech et al., 2010[6]; Cont et al. 2010[7]; Tonzer, 2015). For example, Nagurney (2003) discussed the application network model in lines of research while Allen and Babus (2009) discussed several aspects of finance that have benefited from the network theoretical model.

[6] Embree and Roberts (2009);Chapman and Zhang (2010); Bech et al., (2010) conducted a number of study for the Bank of Canada.

[7] Cont et al. (2010) in the case of Brazil

Concepts based on network models, contagion and interconnectedness are frequently used as in can be linked to the importance of a node in a network (Martinez-Jaramillo et al. 2014). For network models, financial network dynamics is fundamental to the determination of systemic relevance which has been understudied. Theoretically, there is a trade-off within the network topology. This is because interconnections between a series of nodes in a network offer, on the one hand, risk-sharing possibilities which have the tendencies of enhancing financial stability. On the other hand, such nodes may transmit shocks within the network (Tonzer, 2015). For example, Tonzer (2015) conducted a study on the relationship between cross-border linkages among the banking system and financial stability. The results show that on one hand, larger cross-border exposures are likely to increase bank risk, while on the other hand, higher levels of diversification can have counterbalancing effects.

Martinez-Jaramillo et al. (2014) proposed some metrics for systemic risk measurement and measurement. When using this approach, there are some fundamental questions that should be addressed. They include among others: Which network or networks should be used? Is the network of interbank exposures the relevant network to determine systemic relevance? Is the payments system flows network the one that should be used? How do we incorporate the time dimension to study systemic relevance in financial networks?

To study the level of interconnectedness between financial institutions, the interbank network model (INM) can be employed. The model (INM), plays an important role in the analysis of systemic risk and as such, it is important to have relevant data instead of relying on simulation or by making some assumptions, like maximum entropy (Cerutti et al., 2012; Kanno, 2015). This network can spread systemic risk by means of mutual exposures, possibly triggering contagious defaults that are triggered by an individual bank's failure (Kanno, 2015). An analysis of financial networks would alert supervisory authorities or individual institutions about “contagion risk” from the channels through which shocks propagate (Kanno, 2015). Hence, such an analysis serves to test the resilience of a network and to identify systemically significant nodes. Network analysis also provides an empirical tool to test the effectiveness of macro-prudential policies (Kanno, 2015). Although the Network theory has been very useful in the study of financial contagion and risk spill-over, it is quite necessary to highlight its limitations within the systemic risk framework. The fact remains that the systemic risk contribution of an institution cannot be determined by the means of network theory alone, due to the fact that some systemic components might be overlooked (Martinez-Jaramillo et al. 2014).

2.4.1.2 Value-at-Risk (VaR)

Value-at-Risk (VaR) is a vital measure of measuring market risk. It is defined as the maximum possible loss in value of a portfolio of financial instruments with a given probability over a time horizon and at a given confidence interval (Manganelli and Engle, 2001; Kanno, 2015). VaR is therefore used by the researchers to capture and reflect the risk involved in interbank and liquidity exposure (Wang, Chung, & Guo, 2013). The VaR is thus simply a quantile of the return distribution. Although it does not tell us everything about the risk, especially the magnitude of losses on those days when the return is worse than the VaR. McAleer (2009) showed that the management of market risk is monitored by the Basel II Accord and the “Ten Commandments” for optimizing VaR. In the strand of literature ARCH-type models have been used to model VaR (Giot and Laurent 2004). Alexander and Lazar (2006) built on the ARCH-type models and provided the mixture GARCH (1, 1) for exchange returns. More recent literature shows the use of skew-normal mixture and Markov-switching GARCH processes to capture the skewness in the distribution of stock returns (Haas 2010). VaR has been widely used by financial managers due to its simplicity, as it reduces the (market) risk associated with any portfolio to just one number, that is, the loss associated with a given probability. From a statistical point of view, VaR estimation entails the estimation of a quantile of the distribution of returns (Manganelli and Engle, 2001). However, VaR suffers from being unstable and difficult to work with numerically when losses are not “normally” distributed.

2.4.1.3 Expected Shortfall (ES)

Due to the criticism about the adequacy of the VaR framework as a measure of risk, Artzner et al. (1997, 1999) propose, as an alternative measure of risk called the Expected Shortfall (ES). Expected Shortfall (ES) is defined as the expected return conditional on the return being worse than the VaR. The ES which measures the expected value of portfolio returns given that some threshold (usually the Value at Risk) has been exceeded (Manganelli and Engle, 2001).

Extending on the work of Artzner et al. (1997, 1999), Acharya et al. (2010) introduce the systemic expected shortfall (SES) for the measurement of financial institutions' contributions to systemic risk. SES is defined as the probability of a systemic default event and the expected tail loss in case this systemic risk occurs. According to their work, they have found that SES indicator reacts to the financial crisis events with global importance and that the results for the regional sub-samples also capture appropriately the specific regional financial market events. They also introduce marginal expected shortfall (MES) as a measure of banks contribution to systemic risk. That is, it measures losses of an institution in the tail of the system's loss distribution. Like CoVaR, MES only implicitly takes into account the size, the probability of default, and the correlation of each financial institution.

2.4.1.4 Conditional Value-at-Risk (CoVaR)

Conditional value-at-risk (CoVaR), was introduced by Rockafellar and Uryasev (2000, 2002) as an optimizing a portfolio so as to reduce the risk of high losses. As noted earlier, VaR is the most common measure of risk used by financial institutions (Adrian and Brunnermeier, 2011). However, individual institution risk may not necessarily reflect the risk inherent in the entire financial system. Adrian and Brunnermeier (2011) propose the conditional value-at-risk (CoVaR) measure to quantify the risk to the financial system as a whole. CoVaR of an institution is defined as the VaR of an institution i conditional on institution j being in distress. In such cases, firm i is not just concerned about its own risk but also the risk of firm j. CoVaR only implicitly takes into account the size, the probability of default, and the correlation of each institution (Details given in Chapter five). This study adopts the CoVaR model developed by Adrian and Brunnermeier (2011) to measure systemic risk. The CoVaR model is useful in studying risk spillovers as well as capturing systemic risk through the VaR of an institution conditional on other institutions in distress (Drakos and Kouretas, 2015).

2.4.2 Systemic Risk: Empirical Review

Systemic risks manifest through individual institutions or a group of institutions. Individual institutions tend to manage the risks they face and ignore the risk they contribute to the system (externality). Summing up of the risks posed by individual institutions, that are not managed by their respective risk management frameworks, contribute to systemic risk. For example, Duca and Peltonen (2013) assessed systemic risks and predicted events. The study utilized the financial stress index to identify the starting point of a systemic financial crisis. Furthermore, the study utilised the discrete choice model which combines both the domestic and global indicators of financial vulnerabilities to predict systemic risk. They found that the combination of both the domestic and global indicators for measuring vulnerabilities of the financial crisis improves the model's ability to predict the financial crisis.

Patro, Qi, and Sun (2013) examined the relevance and effectiveness of stock return correlations among financial institutions as an indicator of systemic risk. Using daily stock return correlations and default correlations among the 22 largest bank holding companies and investment banks from 1988 to 2008, findings revealed that daily stock return correlation is a simple, robust, forward-looking, and timely systemic risk indicator. Also disaggregating the stock returns into systematic and idiosyncratic components, the result revealed that the correlation increases are largely driven by the increases in correlations between banks' idiosyncratic risks, which give rise to increasing systemic risk. Therefore, regulators and businesses should monitor daily stock return correlations among those large and highly leveraged financial institutions to track the level of systemic risk.

Tomuleasa (2015) conducted an overview of macroprudential policy and systemic risk with reference to the challenges it faces. The analysis performed shows that the financial system is characterized by high sensitivity to the pressures existing in international financial markets. The study emphasized the importance of macroprudential policy in protecting investors, limiting systemic risk and financial stability.

Ellis, Haldane, McAndrews and Moshirian (2014) in their study stated that while attempts have been made to reform four of the five key pillars of banks' operation, (i.e. competition, resolution, supervisory, and auditing and valuation policies), less attention has been paid to the role of bank governance and systemic risk, despite a strong link between governance and risk-taking. The study offers four solutions to strengthen bank governance. First, the regulatory capital base of banks could be increased. Second, the compensation structure of managers could be reformed.

Third, the effort could be focussed on creating and implementing resolution regimes which offer the credible prospect of ‘‘bailing-in’’ creditors in the event of stress and the fourth solution is to reform the structure of company law– for example, by extending control rights beyond shareholders. Furthermore, the study argues that given the diversity of the whole financial system, it is expected that the risks individual financial institutions face are also diverse. It cannot be assumed that the appropriate capitalisation is constant across all risks. While leverage ratios are a useful backstop measure and guard against potential gaming of risk-weights, their appropriate role is as a backstop. The diversity within the financial system also supports the fact that a single measure of systemic risk is unlikely to be universally applicable, nor is a single instrument of financial stability policy.

Paltalidis et al. (2015) study the transmission channel of systemic risk and how financial contagion spread within the euro area banking system using the Maximum Entropy method. Their study captures multiple snapshots of dynamic financial network and uses counterfactual simulations to investigate the propagation mechanism of shocks emerging from three sources of systemic risk: interbank, asset price, and sovereign credit risk markets. As conditions deteriorate, these channels trigger severe direct and indirect losses and series of defaults, whilst the dominance of the sovereign credit risk channel amplifies, as the primary source of financial contagion in the banking network. Systemic risk within the northern euro area banking system is less apparent, while the southern euro area banking system is more prone and susceptible to bank failures provoked by financial contagion. By modelling the contagion path the results demonstrate that the euro area banking system manifests to be markedly vulnerable and conducive to systemic risks. Liao et al. (2015) investigated the effects of systemic risk on macroprudential capital requirement using a panel of correlated regime-switching Merton style network model. The Merton style network model accounts for bankruptcies both through asset correlation and interbank contagion, the result suggests the need for the implementation of macroprudential policy as this will is believed to significantly improve financial stability.
López-Espinosa et al. (2012) employed the CoVaR approach to identify the main factors behind systemic risk in a set of large international banks. Their result revealed that short-term wholesale funding is a key determinant of systemic risk. In contrast, the study found weaker evidence that either size or leverage contributes to systemic risk within the class of large international banks.

Furthermore, the study also shows that asymmetries based on the sign of bank returns play an important role in capturing the sensitivity of system-wide risk to individual bank returns.

Calmès and Théoret (2014) examined how banks react to macroeconomic risk and uncertainty, that is, the relationship between banks' systemic risk and disruption in economic conditions. Using the EGARCH estimation technique, the study revealed that banks tend to behave more homogeneously in line with economic uncertainty. Souza, Silva, Tabak, and Guerra (2016) propose a methodology to measure systemic risk in networks Composed of financial institutions. Stress impact effects obtained from measures that rely on feedback centrality properties are combined with default probabilities of institutions.

2.4.2.1 Systemic Risk and Contagion

One of the major causes of systemic risk that seems to be significant during the recent GFC is contagion. This can be likened to the likelihood that the distress of one financial institution spreads to other institutions within the financial system, and subsequently spurring system-wide crises (Allen and Carletti, 2013). Contagion arises when losses in financial institution A spills-over to other institutions within the system that is linked with institution A. In most cases, central bank's argument for intervention in the system is always the risk of contagion, especially when large systemic banks are involved. For example, according to Bernanke (2008), the buyout of Bear Stearns by J.P. Morgan under the auspices of the Federal Reserve Bank in March 2008 was justified by the possibility that its failure could cascade system-wide failures within the financial system.

Another example is the Lehman Brother's default in September 2008. It was initially believed that the default won't lead to any contagion effect. However, it turned out the other way, as the problem spread to the money market funds, the financial market which was accompanied by a large spillover to the real economy (Allen and Carletti, 2013). This dramatic fall in GDP in many countries underscores the significance of the process of contagion (Allen and Carletti, 2013).

2.4.2.2 Systemic Risk and Macroprudential Regulation

Following a generally acknowledged definition, "macroprudential policy is intended to identify and mitigate systemic risk to the financial sector as by extension the real economy, however, providing such framework is not straight forward (FSB/IMF/BIS, 2009). The need for macroprudential policies arises from two dimensions of systemic risk: the time and cross-sectional dimensions. The time dimension is characterized by the need to restrain financial booms (Borio, 2014). Such financial booms can originate from both the supply and demand sides of agents, and financial intermediary behaviour. For example, the amplification mechanism which is known as "financial accelerator" is mainly related to the demand side (Claessens et al., 2013). However, other mechanisms are related to the supply side, as in the model of Adrian and Shin (2010, 2014), where an initial positive shock that boosts the value of a bank's assets, such as loans and securities, could induce a further increase in debt if the bank targets a certain leverage ratio (Borio, 2014).

On the other hand, the cross-sectional dimension to systemic risk is related to the interconnectedness of financial institution and it became a major point of policy debate after the GFC. The new Basel III regulatory framework, for instance, which targets systemically important financial institutions (SIFI) with specific capital surcharges, aims to reduce negative externalities stemming from interconnectedness (BIS, 2015). An active macroprudential policy will go a long way in reducing the risk-taking behaviour of banks. For example, a countercyclical capital buffer can be actively used to "achieve the broader macroprudential goal of protecting the banking sector from periods of excess credit growth" (BCBS, 2010, pp. 5).
Apart from the direct impact of macroprudential policy tools on bank risk, monetary policy also has an influence on the risk-taking and financial stability (Gambacorta, 2009, Borio and Zhu, 2014, Altunbas et al., 2014, Dell'Ariccia et al., 2010).

Macroprudential tools could, in principle, be used to moderate the risk-taking incentives arising from monetary policy decisions. For instance, Igan and Kang (2011) argue that the impact of a tightening of monetary policy on defaults can be contained by having in place conservative limits on debt-to-income (DTI) ratios. On the other hand, macroprudential measures, such as limits on LTV ratios, can reduce vulnerabilities under the condition that accommodative monetary policy is driving up asset prices. Additionally, higher capital requirements (including countercyclical) or tighter leverage and liquidity ratios may help contain increases in bank risks in response to expected lax monetary policy (Farhi and Tirole, 2012; IMF, 2013).

2.5 EARLY WARNING SIGNAL (EWS) MODEL

A key component of the macroprudential policy framework is a mechanism for early detection of systemic risk. Systemic risk is the risk of disruptions to financial services (including credit intermediation, risk management, and payment services) that is caused by an impairment of all or parts of the financial system and poses serious negative consequences for the real economy. Systemic risk is driven by economic and financial cycles over time, as well as by the degree of interconnectedness of financial institutions and markets (Damodaran and Yejin Carol, 2014). The early warning signal models were developed to estimate the probability of the occurrence of crisis using either quantitative or econometric techniques. Basically, there are two types of EWS models (Bhattacharyay, 2009); namely, the composite indicator model and logit/probit models (Figure 2.4). While the composite indicator creates a composite index using the number of warning signals obtained from a set of macroprudential indicators and directly tying it with a probability of crisis, whereas the probit or logit model computes a probability of the occurrence of a crisis based on the reaction of indicators prior to crises periods (Bhattacharyay, 2009).

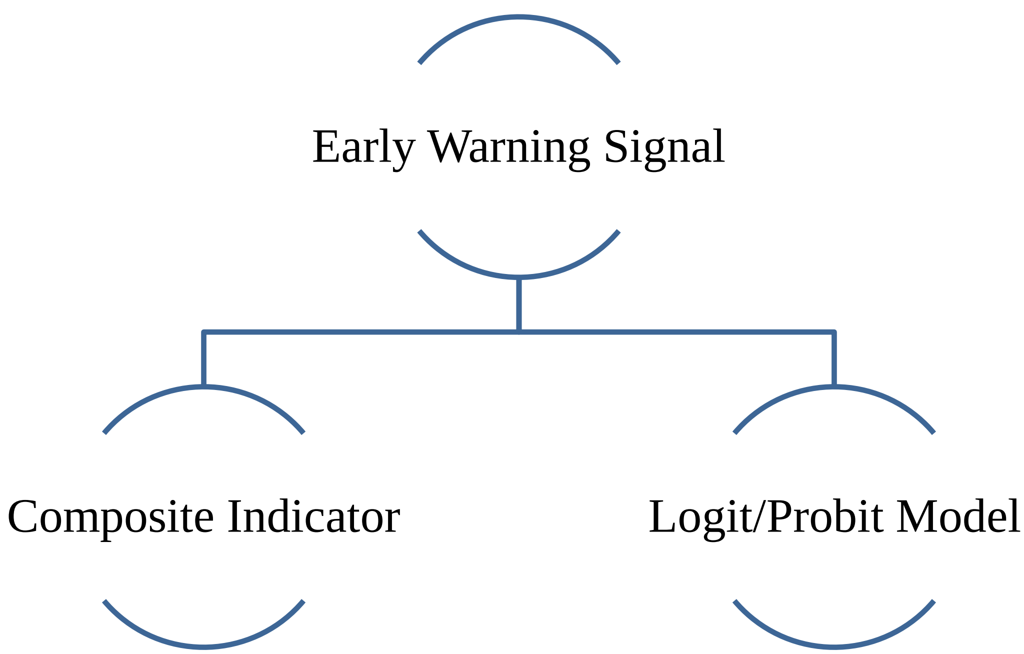


Figure 2. 5: Early Warning Signal Models

A number of studies have been conducted using EWS models which are briefly discussed below:

Wong et al. (2010) employed the probit model for 11 Asia-Pacific countries and their findings revealed that credit growth contributes greatly to the build-up of systemic banking problems. This finding is similar to an earlier study by Demirguc-Kunt and Detragiache (1998) who suggested that banking crises are oftentimes preceded by rapid credit growth within a time-frame of two years. In the case of developed economies, barrel et al. (2010) constructed an EWS model for banking crisis using the logit model. The result shows that house price growth, leverage ratios, as well as liquidity ratio, are determinants of the banking crisis in OECD countries. Similarly, Caggiano et al. (2014) employed a multinomial logit regression for predicting systemic banking crisis in 35 low-income Sub-Sahara African countries. The multinomial logit model is believed to improve the predictive power of the EWS model compared to the binomial logit model because it does not treat the year after the crisis as a non-crisis year. Their findings show that crisis events in low-income countries are associated with low economic growth, the decline in banking system liquidity and expanding foreign exchange net open positions.

Oet et al., (2013) developed a hybrid class of model based on the existing microprudential and macroprudential EWS model for systemic risk that incorporated the structural characteristics of the financial system to explain financial stress. Based on the findings of the study, a model which is known as the Systemic Assessment of Financial Environment (SAFE) EWS was developed to monitor the build-up of macroeconomic stress in the financial market. Also to mitigate inherent uncertainty in the system, a medium-term forecasting specification which gives policymakers ample time to take action was developed. Cumperayot and Kouwenberg (2013) employed the EVT in the context of currency crisis using 18 indicators for predicting a crisis in a sample of 46 countries for the period 1974-2008. The study revealed that economic variables with a stronger association with the exchange rate have a better crisis prediction performance both for the in-sample and out-of-sample estimation.

2.6 FINANCIAL STRESS INDEX (FSI)

Although there is no consensus on the definition of financial stress, it is commonly accepted as a disruption of the functioning of the financial market (Aklan, Cinar, and Akay, 2015). The FSI is a single aggregated index developed to reveal the systemic characteristics of financial instability and as well to gauge the vulnerability of the financial sector to both internal and external shocks. The FSI has been a veritable measure for gauging financial market stress as well as its severity since spikes in the FSI corresponds to the episodes of severe financial crisis. It can also be referred to as shocks with negative effects on the real economy (Illing and Liu, 2006). One common characteristic of financial stress is the increasing uncertainty of creditors and investors about the real value of financial assets which in turn leads to increased volatility of asset prices. Calculating the financial stress index is important not only for evaluating macroeconomic conditions but also to determine the source(s) of fragility in the financial sector. There is a dearth of literature on the financial stress index. Even the available ones differ based on methodologies and countries.

The FSI also provides information on systemic stress which is not captured by the individual market stress measures as well as making a decision about the release of the counter-cyclical capital buffer (Huotari, 2015). That is to say, the FSI provides the information needed by policy makers and central banks to develop counter-cyclical buffer to cushion the effect of the crisis. It is believed that the principal component analysis (PCA) method, as well as the portfolio-theoretic approach, produced an index that reacts to the same known stress events (Huotari, 2015). The variance-equal weighting method produced an index that shows significant stress at the end of the sample and this is difficult to justify (Huotari, 2015). The systemic nature of the stress event is usually better captured by the PCA (Hakkio and Keeton, 2009). This account for the use of PCA in this study.

Illing and Liu (2006) developed an index to measure financial stress for the Canadian financial system, using a continuous variable with a spectrum of values where extreme values correspond to periods of financial crises. Using daily frequency covering the equity markets, bond markets, foreign exchange markets as well as the banking sector, they aggregated the stress indicators into a single index by weighting the variables by the size of each market to which they pertain. Hakkio and Keeton (2009) built a comprehensive index for financial stress in the U.S. economy known as the Kansas City Financial Stress Index (KCFSI). Using the principal component analysis alongside the equal-variance weighing method as well as using eleven indicators based on the representation of the features of financial distress, the study revealed that financial stress is the factor most responsible for the co-movement of the eleven variables.

Cardarelli et al., (2011) using a refined methodology by Illing and Liu (2006), examined the impact of financial stress on economic activity, and the findings revealed that financial turmoil characterized by banking distress is more likely to result in severe downturns compared to stress mainly in securities or foreign exchange markets. Using the variance-equal weighing method, they construct a monthly FSI for 17 advanced economies. Building on the work of Cardarelli et al. (2011) and using the same methodology, Balakrishnan et al. (2011) developed FSIs for 18 emerging economies. Also, Oet et al. (2011) developed a FSI for the United States called the Cleveland Financial Stress Index (CFSI). The CFSI was developed using daily data from 11 components reflecting four financial sectors namely: credit markets, equity markets, foreign exchange markets, and interbank markets. Most of the CFSI components are spreads (i.e. interbank liquidity spread, corporate bond spread, liquidity spread) and two of the remaining CFSI components are ratios, and one is a measure of stock market volatility.

Furthermore, Hollo et al., (2012) developed a Composite Indicator of Systemic Stress (CISS) with the application of basic portfolio theory to the aggregation of market specific sub-indexes. The portfolio-theoretic aggregation method takes into account the time-varying cross-correlations between the sub-indexes. The CISS measures stress in the financial system in the euro area. Using 15 individual stress measures to construct market specific sub-indexes, the study revealed that the CISS, in comparison with the previous FSIs, places more weight on conditions in which stress prevails in some markets simultaneously.

Islami and Kurz-Kim (2013) also develop a composite FSI for the euro area. The authors base their FSI on its ability to predict developments in the real economy and select risk variables based on their correlation with economic activity, measured by industrial production. Also, Sinenko, Titarenko and Arins (2013) developed a methodology for measuring the Latvian financial stress index and also analysed the nature of financial stress. The methodology developed reflects the changes in the Latvian financial system. It also helped in signalling periods of elevated stress as well as periods of excessively vigorous and imbalanced development of the financial system. The Bank of Latvia has been using the FSI as one of the elements of Latvia's financial system stability monitoring framework since 2010. Kondratovs (2014) examined the fragility of the financial system of Latvia to the fluctuations in the global economy and changes in the direction of international capital flows by creating complex financial system stability index. Findings of the study revealed that fall in the stability level of the Latvian financial system started in 2002 and became worse in 2005 which informed the need for policymakers to be more actively involved in preventing growing risk to the economy.

Huotari (2015) in his study proposed a financial stress index (FSI) which is aimed at reflecting the functionality of Finland financial system and as well provided an aggregate measure of financial stress in the money, bond, equity and foreign exchange markets and the banking sector. Information from all these markets was combined through the FSI composite index to provide a single measure of stress in the financial system. The FSI also provides information on systemic stress which is not captured by the individual market stress measures as well as making a decision about the release of the counter-cyclical capital buffer. That is to say, the FSI provide the information needed by policy makers and central banks to develop counter-cyclical buffer to cushion the effect of the crisis.

Iachini and Nobili (2016) in their study introduced an indicator for measuring systemic risk in the Italian financial market using portfolio aggregation theory method. This portfolio aggregation was used to capture the systemic dimension of liquidity stress. The result shows that the systemic liquidity risk indicator adequately captured extreme events that were characterized by high systemic risk. In the case of emerging markets such as Russia, China, India, Brazil, South Africa, Indonesia, Turkey, Mexico, Malaysia, Thailand, Philippines, Chile, Columbia as well as Peru, Stolbov and Shchepeleva (2016) employed the PCA approach to calculate the FSI using six variables, the results of the study show that the FSI for most emerging markets exhibited surge around September – October 2008 and this is assumed to have been caused by the emergence of the GFC (Stolbov and Shchepeleva, 2016).

2.7 STRESS TESTING

The term stress testing, although, is well known and used in the field of medicine and engineering, gained prominence in the field of economics and finance after the GFC (Borio, Drehmann and Tsatsaronis, 2012). Since then, it has come to be recognized as a banking regulation toolkit, with several regulators, developing and implementing concurrent bank stress testing frameworks (Dent, Westwood and Segoviano, 2016). Basically, stress tests are used to measure the resilience or stability of an entity or system under imaginary adverse scenarios, that is, the systemic measure of what an entity or system may lose during a hypothetical severe economic recession (Borio, Drehmann and Tsatsaronis, 2012; Berner, 2016; Cortés, 2018). In other words, during such a test, the capacity of the financial institution to withstand extreme adverse economic conditions is analysed.

The result of such test is then converted into a forecast of its regulatory capital ratios conditional on different stress scenarios and used by central banks and regulators to measure risks and manage them through the setting of prudential policy to promote resilience (Dent, Westwood and Segoviano, 2016; Cortés, 2018). According to Berner (2016), stress tests can be used as a tool for risk management at the financial firm level and as well be employed to calibrate macroprudential tools, designed for building resilience in the entire financial system. It adds a macroprudential dimension to the supervision of banks through the evaluation of the aggregate capital position of banks (Bernenke, 2013).

Stress testing can generally be classified into two broad groups, namely: Micro and macro. Micro stress testing was initially employed to test the performance of individual portfolios or the stability of individual institutions, while, macro stress testing is used to test the resilience of groups of financial institutions that, combined together, can have an impact on the economy as a whole (Borio, Drehmann and Tsatsaronis, 2012). The tests are aimed at providing a quantitative measure of the exposure of a country's financial system to diverse macro-financial setups as well as to complement the insights compiled from other components of the assessment (Dent, Westwood and Segoviano, 2016). Over the years, central banks and supervisors have employed stress (micro) test to assess the resilience of individual banking companies to adverse macroeconomic and financial market conditions as a way of gauging additional capital needs at individual firms and as means of assessing the overall capital adequacy of the banking system (Hirtle, Kovner, Vickery, & Bhanot, 2014; Berner, 2016). Micro stress tests were initially used to check for the performance of portfolios of the strength of firms. However, in recent times, such techniques have been used to ascertain the stability of groups of financial institutions (Borio, Drehmann, & Tsatsaronis, 2014).

Stress testing is very important for regulators in terms of evaluating the sufficiency of reserves and capital, examining possible weaknesses or threats outside the regulatory perimeter, reinforcing firms' risk management, and assessing potential system vulnerabilities (Berner, 2015). At the macro level, stress testing is aimed at assessing structural vulnerabilities and risk exposure within the financial system that could probably cause systemic failure. A system-wide stress test is therefore defined "as a measure of the risk exposure of a group of financial institutions to an 'exceptional, but plausible' stress scenario" (Sorge and Virolainen, 2006: Pp 114). It is often used as a complement to the individual financial institution stress test.
Macro stress testing has proved a useful instrument to help identify potential vulnerabilities within the banking sector, shed light on potential sources of systemic risk and to gauge its resilience to adverse developments (Jakubík, P. and G. Sutton. 2011; ECB, 2013). To measure the resilience of the entire financial system against severe yet plausible adverse scenarios, macro stress tests link macro-financial variables with the health of financial institutions (ECB, 2013).

Over the years, there has been an improvement in the understanding of the functioning of the financial system as well as the ability to gauge financial activity and spot vulnerabilities (Berner, 2015). However, there is a need for us to understand how the financial system fails to function under stress, to spot vulnerabilities in the shadows, and to gather and standardize the data needed for analysis and policymakers' responses to identified threats (Berner, 2015). As the main target of stress testing is how risk is transmitted, Network and Agent-based modelling will be a better method to move stress test towards a system-wide framework (Berner, 2016).

According to Kanno (2015), macro stress tests for credit risk are carried out in three phases. In phase 1, the macroeconomic variables are envisaged, given the predefined stress scenario at some risk horizon. In step 2, the impact of stressed macroeconomic variables is expected to produce credit risk parameters of a financial institution, usually in the form of Probability Default (PD) and Loss Given Default (LGD). Finally, at phase 3, the impact of the scenario highlighted is evaluated to estimate the value of the financial institution at risk (VaR), given the credit risk parameters, (Kanno, 2015; Ouma, 2016).

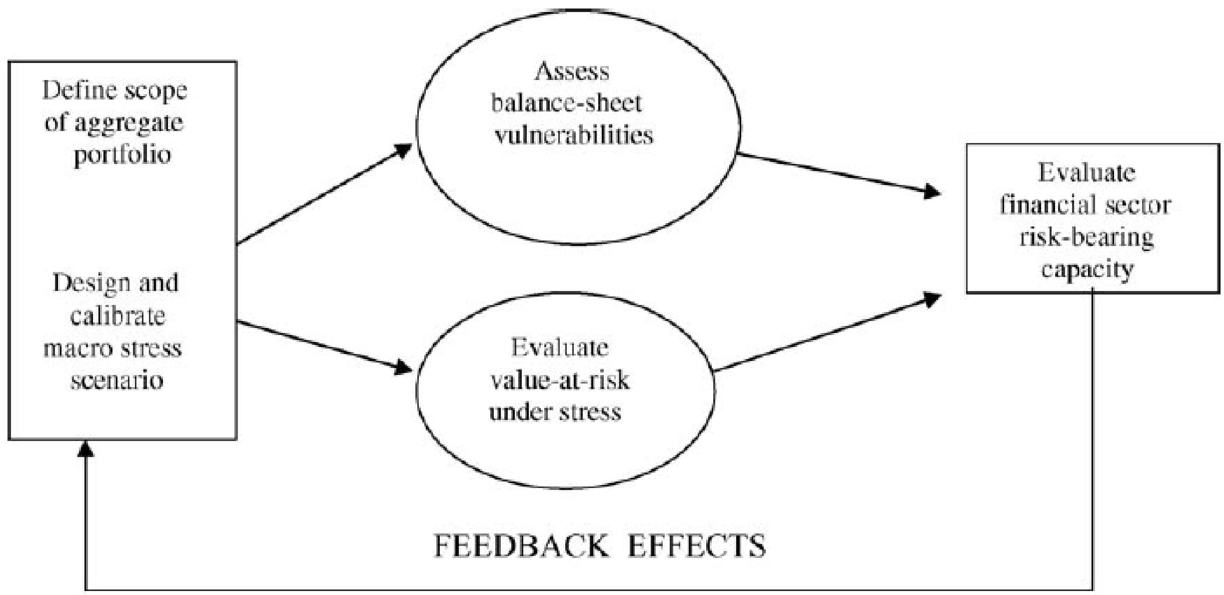


Figure 2. 6: An Overview of Macro Stress Testing Procedure.

Source: Sorge and Virolainen (2006)

As seen in Figure 2.5, the first step in macro testing is to define the scope of analysis with respect to the appropriate set of institutions and portfolios; after which a macroeconomic stress scenario will be designed and calibrated. The third step will be to quantify the direct impact of the simulated scenario on the solvency of the financial sector, either assessing balance sheet vulnerabilities during macroeconomic downturns or integrating the analysis of multiple risk factors into a probability distribution of aggregate losses. The fourth step is the interpretation of the results to gauge the overall risk-bearing capacity of the financial system. Lastly, the feedback effect both within the financial system as well as from the financial system to the economy is accounted for (Sorge and Virolainen, 2006; Berner, 2016). Nevertheless, due to the significant role of banks in the supply of credit, and as well their reliance on short term funding, macro stress tests usually focus on a country's banking sector. Stress testing involves a number of elements and they include: 1). Risk exposure subjected to stress; 2). The scenario that defines the shocks that stress those exposures; 3). The model that maps those shocks to an outcome and tracing their propagation through the system; 4). Testing the solvency or measuring the outcome (Borio, Drehmann and Tsatsaronis, 2012). The approaches to stress testing are described in the following section.

2.7.1 Approaches to Stress Testing

There are two stress testing approaches, namely: a top-down approach and bottom-up.

1) **Top-Down (TD) Approach** to stress testing: The TD approach to stress testing is aimed at providing regulators with the magnitude of loss in an adverse scenario. For example, if the equity market falls by 25 percent, what will be the magnitude of the loss.

2) **Bottom-Up (BU) Approach** to stress testing: the BU approach which is also known as the reverse stress test is aimed at identifying the event that could have led to the loss. It is basically the opposite of the TD approach.

2.7.3 Classification of Stress Testing Technique

Stress testing exercise is categorized into two broad groups, namely: 1) scenario analysis and 2) sensitivity analysis (Figure 2.6).

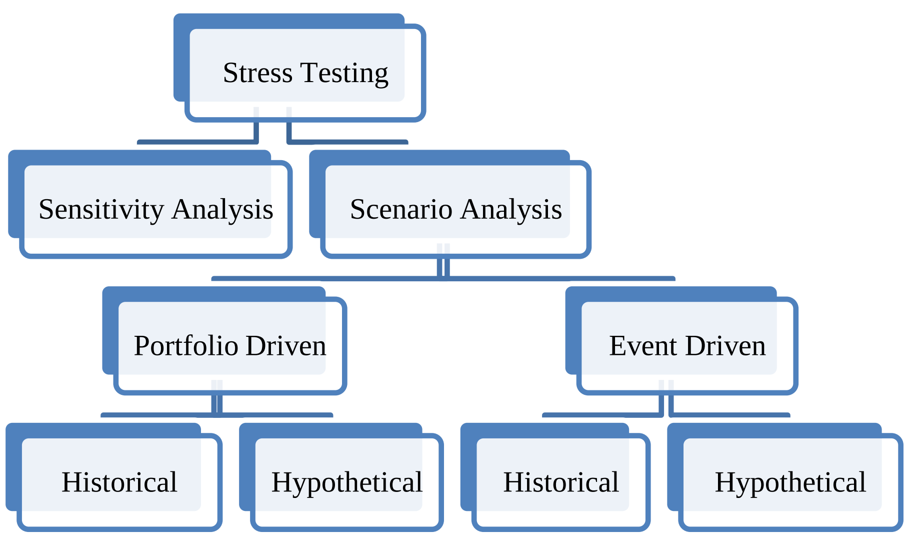


Figure 2. 7: A Classification of Stress Testing Technique Framework

Source: Author’s Compilation

2.7.3.1 Sensitivity Analysis

Sensitivity analysis sees the impact of changing one factor on the portfolio or profile at a given time. It is simplistic in the sense that for testing purposes factors only change one by one. While in real life factors usually change together and not in isolation. It also does not tell us why the factor is changing or the probabilities associated with such an occurrence.

2.7.3.2 Scenario Analysis

Scenario testing covers for the deficit of the sensitivity analysis. It includes variables that explain why the change is happening and to what extent. It allows for interaction between factors. By not holding all factors constant, correlations between different explanatory variables are taken into account. The scenario analysis is further divided into portfolio driven scenario and event-driven scenario.

1) Portfolio-Driven

Portfolio-driven scenarios are derived by considering what the vulnerabilities within a particular portfolio are.

2) **Event-Driven**

Event-driven scenarios are derived by the considering specific adverse external (often economic) scenarios and determining the impact of such events on the performance of a particular portfolio.

2.7.4 Types of Financial System Risk

Financial risk is the likelihood of financial loss or gains as a result of unexpected changes in underlying risk factors (Dowd, 2011). According to literature, there are five main types of financial system risk and they include macroeconomic risk, market risk, credit risk, funding and liquidity risk, and contagion (Figure 2.7). Monitoring these risks is very important in ensuring the soundness and safety of the financial system (Berner, 2016).

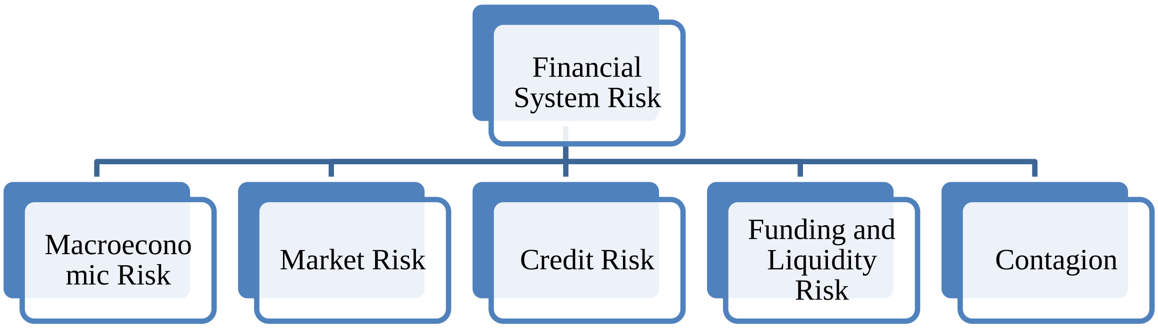


Figure 2. 8: Types of Financial System Risk

Source: Author's Compilation

2.7.4.1 Credit Risk

Credit risk is the risk of loss emanating from the failure of a counterparty to make a promised payment (Dowd, 2011). In order words, it relates to the potential loss due to the inability of a counterparty to meet its obligations. It has three basic components: credit exposure, probability of default and loss in the event of default. Yield spreads can be used to measure the credit risk levels based on market assessment.

2.7.4.2 Macroeconomic Risk

Macroeconomic risk relates to economic wide factors that may impact on the performance of the economy. It could be economic and political factor risk that affects governments including unemployment, inflation, prices, export/import, and market factors that can influence investment, assets and company evaluations[8]. Others include macroeconomic volatility, business cycle fluctuation, or market volatility.

2.7.4.3 Liquidity Risk

Liquidity risk is caused by an unexpectedly large and stressful negative cash flow over a short period. For example, if a firm has highly illiquid assets and suddenly needs some liquidity, it may be compelled to sell some of its assets at a discount.

[8] See https://globalriskinstitute.org/research/macroeconomic-risk/

2.7.4.4 Market Risk

Market risk estimates the uncertainty of future earnings, due to the changes in market conditions (Manganelli and Engle, 2001). It can further be classified into interest rate risks, equity risks, exchange rate risks, commodity price risks, etc, depending on whether the risk factor is an interest rate, a stock price (Dowd, 2011)

2.7.4.5 Contagion

Contagion tests are focused on interbank linkages and spillover effects. It is defined as the risk that financial difficulties at one or more bank(s) spill over to a large number of other banks or the financial system as a whole (Schoenmaker, 1996). In order words, it is a situation where a shock in a particular financial institution, economy or region spreads out and affects others by way of, say, price movements (Claessens et al., 2001; Forbes and Rigobon, 2002). A good example of contagion is the case of the Lehman Brothers bankruptcy on September 15, 2008.

2.7.5 Historical Development of Stress Testing

Although, for many regulatory authorities, the stress testing exercise was introduced as part of the IMF and World Bank Financial Sector Assessment Programs (FSAPs) in 1999, it actually dates back to the early 1990s, when banks began a small scale stress tests of their trading activities (Foglia, 2009; Dent, Westwood and Segoviano, 2016). The FSAP of which (macro) stress tests have been a major component, was introduced in 1999 following the Asian crisis (Dent, Westwood and Segoviano, 2016). The FSAP is made up of two components, namely: 1) the financial stability assessment (which is the responsibility of the IMF) and the financial development assessment which is the responsibility of the World Bank. The aim of the FSAP which is a comprehensive and in-depth analysis of a country's financial sector is to bring together Bank and fund expertise to help countries reduce the likelihood and severity or vulnerabilities of the financial sector to the financial crisis. According to the World Bank, the FSAP is based on three approaches, namely; i) The soundness of a financial system versus its vulnerabilities and risks that increase the likelihood or potential severity of financial sector crises; ii) A country's developmental needs in terms of infrastructure, institutions and markets, and iii) A country's compliance with the observance of selected financial sector standards and codes. It is noteworthy that since the inception of the program, a total of 144 member countries has requested and undergone FSAPs.

BEFORE THE GFC	
Early 1990s	• Bank begins small scale stress tests of their trading activities
1996	• Market risk amendment to the Basel Capital Accord
1999	• IMF and World Bank lunch the Financial Sector Assessment Program (FSAP)
Early 2000s	• National central banks and supervisory authorities begin to develop their own bank stress test
2004	• Basel II introduces requirement for credit risk stress testing banks
AFTER THE GFC	
February 2009	• Federal Reserve begins the Supervisory Capital Assessment Program (SCAP)
May 2009	• Committee of European Banking Supervisors (CEBS) begins inagural EU-wide stress test
2011	• Federal Reserve begins Comprehensive Capital Analysis and Review (CCAR) programme which incorporates an anuual bank stress test
2014	• Bank of England begins annual stress-testing program
2017	• Bank of England stress test adding an exploratory scenario in addition to the annual cyclical scenario
2018	• European union stress test

Figure 2. 9: Historical Development of Stress Testing

Source: Author's Compilation

2.7.5.1 Stress Testing before the GFC

Macro stress testing before the GFC was focused on capturing the impact of severe, but plausible shocks on the entire financial as well as the wider economy compared to the micro stress test which focused on the risk faced by individual financial (Dent, Westwood and Segoviano, 2016). As noted earlier, the use of stress tests as a tool started in the early 1990s and was spurred by their use in the FSAP, although policymakers were considering the possible impact of hostile events on the financial system before then. The program identified the damaging impacts of that financial instability can have on the financial system and the economy as a whole as seen in the financial crises of the 1980s and 1990s, and thus focused on the system-wide stability and a wide range of risks, namely: credit risk, interest rate risk as well as exchange rate risk (Kapinos, Mitnik and Martin, 2015; Dent, Westwood and Segoviano, 2016). The FSAP, has, therefore, tests spurred a number of research interest which motivated quite a number of regulators to commence conducting regular independent stress testing of their financial systems (Kapinos, Mitnik and Martin, 2015). This is usually done by updating the existing FSAP scenarios. During this period, the concurrent stress test (which had evolved over time) conducted by policymakers seldom had a direct impact on regulatory or financial policy, but their outputs are usually incorporated into broader financial stability assessments (Dent, Westwood and Segoviano, 2016).

However, during one of the FSAPs conducted for Iceland, the stress test was seriously criticized for failing to adequately measure the level of resilience of their financial system. Based on its assessment of Iceland's financial system in August 2008, the IMF concluded that "the financial indicators of the Icelandic banking system were above the minimum regulatory requirements and indicated that the stress tests had suggested that the system was resilient" (Groepe, 2017). However, shortly after that, the Iceland banking system collapsed. Another example of the pre-crisis stress testing failure was the stress test conducted by the Office of Federal Housing Enterprise Oversight (OFHEO) on the interest rate and credit risk of Fannie Mae and Freddie Mac[9] in 2002.

The output of the teat was used to ascertain the capital adequacy level of the firms. According to Frame et al. (2015), the stress test was "a spectacular failure," due to the fact that the test

[9] The two firms are U.S. government-sponsored enterprises (GSEs) and they are central to financing the U.S. housing market.

recommended the firms' capital was adequate till just a few months before they became insolvent and were placed into conservatorship by the U.S. government.

As much as it is easy to criticize the failure of the stress test from spotting the coming danger, the major lesson from the crisis only raised some important question on what can and cannot be expected of stress test both now and in the future (Bernenke, 2013; Groepe, 2017). Frame et al. (2015), however, suggested that 1) the model should be conceptually evaluated, updated and re-estimated regularly in order to maintain its rigour and accuracy; 2) regulators must ensure that appropriate scenario is selected, and 3) regulators and stakeholders involved in stress testing should be careful with the assumptions made with respect to the balance sheet behaviour.

2.7.5.2 Stress Testing after the GFC

The GFC exposed significant weaknesses in risk measurement and management across the financial sector. The major objective of the regulators had to shift from mere assessing vulnerabilities in tranquil periods to supporting crisis management and resolution (Borio, Drehmann and Tsatsaronis 2012). The first major stress test after the crisis is the Federal Reserve's Supervisory Capital Assessment Program (SCAP). This program is the first of its kind that the Federal Reserve had conducted concurrently across the biggest US banking institutions.

This exercise, which was introduced in 2009 and which examined if the US banks had sufficient capital to absorb losses and continue to operate under adverse stress scenario, had been widely believed to be credible and successful, and has since then, served as a benchmark for the techniques and scale of stress testing (Borio, Drehmann and Tsatsaronis 2012; Kapinos, Mitnik and Martin, 2015). The SCAP (stress test) marks an important milestone in the GFC as it provided investors with facts about potential losses at banks (Bernenke, 2013; Groepe, 2017). This information provided by the regulators assisted in restoring investors' confidence in the system. The SCAP is generally considered to have contributed immensely to the resilience and stabilization of the US financial system, and also restoring broader market confidence (see Krugman (2014), Schuermann (2013) and Zhang (2013)). The achievement of the SCAP was trailed by an upsurge of frameworks for regular concurrent stress testing across central banks and supervisory authorities. Presently, the Federal Reserve has two different supervisory programs that depend on stress testing, namely: the Dodd-Frank Act (DFAST) stress test as well as the

Comprehensive Capital Analysis and Review (CCAR) (Bernenke, 2013; Groepe, 2017). The DFAST is aimed at quantitatively assessing the level of banks' capital during adverse economic and financial scenarios, while the CCAR combined the quantitative results with a more qualitative assessment of the capital planning process used by banks (Kapinos, Mitnik and Martin, 2015). In 2012, the DFAST required the largest American banks to perform stress testing, however, in 2014, medium size firms with asset size of $10-$50 billion were included (Ouwa, 2016).

For the European Union (EU), the maiden EU-wide concurrent stress test was carried out in late 2009 under the supervision of the Committee of European Banking Supervisors (CEBS) (Borio, Drehmann and Tsatsaronis, 2012). Subsequently, a series of stress tests were carried out, for example, in 2010 and 2011, stress tests were conducted under the supervision of CEBS and EBA respectively. These stress tests were initially meant to serve as complements to the stress test conducted by banks[10] before the bank of England launched its own concurrent stress testing programme in 2014 (Borio, Drehmann and Tsatsaronis, 2012). In the United Kingdom (UK), the Bank of England (BoE) conducted a stress test which included two stress scenarios together with the annual cyclical scenario. The aim of this additional scenario is to consider how the UK banking system might evolve if recent headwinds to bank profitability persist or intensify. It included weak global growth, persistently low-interest rates, and stagnant world trade; it has a seven-year horizon to capture these long-term trends (Groepe, 2017).

2.7.6 Stress Testing: African Experience

As noted earlier that stress testing is important to measure the effect of adverse scenarios on the economy. A brief account of stress testing experience for emerging African economies which this study focused on is given in the following subsections.

2.7.6.1 South Africa

The IMF carried out a comprehensive stress testing exercise for South Africa is part of the 2014 FSAP. The exercise focused mainly on the solvency and liquidity stress testing for the banking

[10] Stess tests conducted by banks were carried out on a non-concurrent basis and they are supervised by the former Financial Services Authority (FSA).

and insurance sectors. Based on its findings, the IMF suggested that the SARB develop a macroprudential stress-testing framework (following a top-down approach) to complement the existing bottom-up exercises conducted by banks (Greope, 2017). In response to the IMF recommendation, the SARB created a Stress Testing Division within its financial Stability Department in January 2015. The division conducted a full stress-testing exercise on the domestic operations of the major banks in South Africa during the period from December 2015 to April 2016 with six foremost banks[11] participating in the exercise (Groepe, 2017). The banks were also mandated to carry out their own (bottom up) stress test with a specific focus on credit risk, while the SARB also carried out similar exercise using the top-down approach with a similar scenario. The results of the bank stress tests were aggregated and compared with that of the reserve bank. The results show that the banks are adequately capitalized to withstand significant credit losses throughout the stress scenarios. This is as a result of the high capital buffers that are predominant in the banking system.

2.7.6.2 Nigeria

In a similar manner, the Central Bank of Nigeria (CBN) in conjunction with the IMF's FSAP team, conducted a banking industry stress test in 2013 using the top-down sensitivity analysis of solvency risk and liquidity risk, bottom-up sensitivity analysis, and network analysis of contagion risk or interbank exposure. The result showed that the average capital adequacy ratio (CAR) declined from 18.5 to 17.3 for a 100 percent increase in NPLs with only one bank falling below the 10 percent CAR regulatory requirement (IMF, 2013). This constitutes 2 percent of the total banking sector assets. When the NPL was increased to 200 percent the average CAR declined by 3.3 basis points to 15.2 percent with 3 banks falling below the minimum CAR threshold, with a total banking sector loss of 27.7 percent of total capital. The total banking sector loss increased to 33.9 percent when the NPL was raised to 300 percent while 7 banks fell below the minimum CAR threshold (IMF, 2013).

Furthermore, the Central Bank of Nigeria (CBN) solely conducted a banking industry stress test in 2016 and 2017 to capture the resilience of the Nigerian banking system as well as to address macroprudential concern using both top-down and bottom-up approaches. The stress test covered

[11] These banks make up more than 80% of the total banking sector's assets in South Africa.

23 commercial banks and merchant banks with a specific focus on credit, liquidity and interest rate risk channels in 2016, while in 2017, 20 commercial banks and 4 merchant banks were covered with a specific focus on credit, liquidity, interest rate and contagion risks (CBN, 2016; 2017). The industry was classified into three major groups, namely: 1) large: comprises of banks with assets greater or equal to (≥) N[12] 1 trillion, 2) medium: comprises of banks with assets greater than (>) N 500 billion, but less than (<) N trillion; and 3) small: comprises of banks with assets less than or equal to (≤) N 500 billion (CBN, 2017).

The credit risk stress test revealed that only large banks could withstand a further deterioration of their NPLs by up to 50 per cent. Nonetheless, none of the groups could withstand the effect of the most severe shock of a 200 per cent increase in NPLs as their post-shock CARs fell below the 10 per cent minimum prudential requirement (CBN, 2016; 2017). Also, the liquidity test that was carried out using the Implied Cash Flow Analysis (ICFA) and Maturity Mismatch/Rollover Risk revealed that after a one-day run, the liquidity ratio of the banking industry fell to 31.5 per cent from the 48.1 percent pre-shock position, and to 11.8 and 7.9 per cent after a 5-day and cumulative 30-day run, respectively (CBN, 2017). This shows that the banking industry is significantly vulnerable to liquidity risk. Furthermore, the analysis of the banks' unsecured interbank exposures indicated that one bank failed the CAR test after 100 percent assumed default of its interbank exposures (CBN, 2017).

Farayibi (2016) also conducted a bottom-up stress test for the Nigerian banking sector between 2004 and 2014 employing error correction mechanism (ECM) and the ordinary least square methodologies (OLS). The result revealed that the Nigerian banking sector is vulnerable to various types of risks both within and outside the country, such as credit risk, exchange rate risk etc. According to the study, "bank stress management in Nigeria is sensitive to total credit to the economy, nonperforming loan, and loan-to-deposit ratio because they impact negatively towards banks' profitability" (Farayibi, 2016:11) This implies that these variables need to be monitored so as to ensure that the financial system is stable.

[12] Nigeria naira

2.7.6.3 Egypt

In the case of Egypt, the FSAP team from the World Bank and IMF visited Egypt between May 6 and May 21, 2007, to update the assessment of the Egyptian FSAP which was conducted earlier in the third quarter of 2002. The result of their assessment showed that the average CAR in commercial banks rose from 5.4 percent in 2004 to 5.5 percent in 2006 and that the risk-weighted capital adequacy ratio has improved from 11.4 to 15.1 percent (World Bank, 2007). Recently, the Central Bank of Egypt (CBE) also conducted a comprehensive stress test prior to the devaluation of its currency to confirm if the banking sector capital and liquidity buffers were adequate enough to withstand the devaluation and higher interest rate. The results indicated that the banking system was sound, although, there were indications that, in the event of a severe adverse shock, the capital adequacy of small banks could fall below the Basel-recommended 10 percent threshold (IMF, 2017). The two largest public banks have capital adequacy ratios above the prudential requirements, but both banks may require additional capital in the future to support strong lending growth and IT upgrades (IMF, 2018).

2.7.6.4 Kenya

In the case of Kenya, the Central Bank of Kenya (CBK) the Cihak Stress Testing Framework was adopted for conducting both Macro-and Micro-prudential Stress Testing in line with East Africa Community Monetary Affairs Committee (EACMAC) of Central Bank Governors' Decision during the 16th MAC meeting held in May 2013 in Kampala, Uganda (CBK, 2014). The major risk that the stress tests are credit risk, liquidity risk, interbank (pure contagion risk), interest rate risk as well as foreign exchange risk.

The results of the credit risk stress test show that large banks are more resilient and that it would require a significant rise in the level of Non-performing loans for them to fail to meet the minimum statutory CAR. Only two small banks fell below the minimum CAR ratio of 12 percent with 10.1 percent and 10.9 percent respectively (CBK, 2014). The result further revealed that only two small banks failed to meet the minimum liquidity requirement of 20 percent in the event of a one-off 5 percent deposit withdrawal. While, a 5 percent sudden decline of the Kenyan shilling would not affect banks as all the banks comply with the 10 percent foreign currency exposure limit (CBK, 2014).

2.8 CHAPTER SUMMARY

An overview of systemic risk and financial stability was given in this chapter. This chapter was divided into 8 sections. The comparison between microprudential and macroprudential policies was highlighted in Section 1. Issues around economic stability and how it relates to monetary policy as well as the macroprudential policy was discussed in Section 2. Under the section, policy strategies before and after the GFC were highlighted. In Section 3, financial stability issues as it related to macroeconomic development and banking sector reforms in some selected African economies were discussed. Both theoretical and empirical review on systemic risk was presented in Section 4, while discussions on the development of an early warning signal model were discussed in Section 5. Section 6 was dedicated to discussing issues on financial stability, while stress testing discussions were presented in Section 7. Under this section, the types, approaches and historical development of stress testing were highlighted. The chapter summary is presented in Section 8.

CHAPTER THREE

DEVELOPING FINANCIAL STRESS INDEX FOR THE EMERGING AFRICAN ECONOMIES

The objective of this chapter is to develop a financial stress index (FSI) for the emerging African economy. The FSI is a single aggregate indicator that is constructed to reflect the systemic nature of financial instability and as well to measure the vulnerability of the financial system to both internal and external shocks. The chapter is divided into four broad sections. A brief history of FSI is highlighted in Section 1, followed by the procedure for the construction of FSI which was discussed in Section 2. Estimation result is presented in Section 3 while the chapter summary is presented in Section 4.

3.1 A BRIEF HISTORY OF FSI

The financial stability index is aimed to reveal the functionality of the financial system due to uncertainty or stress and provide an aggregate measure of financial stress in the financial system as a whole which includes the money market, bond market, foreign exchange market etc. (Huotari, 2015). In order words, developing FSI will enable regulatory authorities, government, policymakers and other stakeholders to understand the general condition of the financial sector. The financial stress index is a composite index that aggregate information from these markets to provide a single measure of stress for the whole financial system (Huotari, 2015). This makes it easier to monitor the financial system and determines the date of the financial crisis. The FSI is a highly useful and appropriate dependent variable in an early signal warning model and also it is used to gauge the effectiveness of government measures to mitigate financial stress. It is also useful by macroprudential authorities in their macroprudential decision making. Generally, FSIs are mostly calculated on a monthly basis for developed countries like the USA.

There have been several indicators that have been developed since the 1980s, such as the slope of the yield curve, which is based on the difference between long-term and short-term interest rate, credit risk measured by commercial paper-Treasury bill spread, stock markets (Aykut, 2013). The first broader financial condition, measure as introduced by the Bank of Canada in the mid-1990s named monetary condition index (MCI) which is the weighted average changes in interest rates and exchange rate relative to their value during the base period (Ekinci, 2013). MCIs are used by policymakers as measures of monetary conditions in the economy. Soon after that, several of such similar indexes were being used as for monetary policy decisions by a number of central banks such as that of Canada, New Zealand and Sweden (Ekinci, 2013). Several other indicators such as stock price and real estate were incorporated into the MCI, which made it broader and now being referred to FSI.

For example, the Bloomberg FCI which is calculated using ten variables covering the money market, bond market as well as the equity market is believed to be a suitable measure to watch financial conditions since it is accessible to many financial markets and updated on a daily basis from 1991 (Rosenberg, 2009). In contrast to the Bloomberg FCI, Citi FCI, which is available from 1983 is calculated using six financial variables, including corporate spreads, money supply, equity values, mortgage rates, the trade-weighted dollar, and energy prices (D‘Antonio, 2008). The nominal values in Citi FCI are deflated and the indicators include various transformations and lags that are used for anticipating movements in the coincident index at a horizon of roughly six months. In a similar manner, the Deutsche Bank FCI also starts in 1983, although it differs with respect to the number of variables and methodology used. The index is made up of seven variables including exchange rate, bond, stock, and housing market indicators and calculated using principal component analysis (Hooper, Mayer and Slok, 2007; Hooper, Slok and Dobridge, 2010). In 2008, the OECD developed its own FCI which starts from 1995 by aggregating six financial variables and weighting them according to their effects on GDP for four to six quarters (Guichard and Turner, 2008). This FCI differs from other FCIs in that it included variables for tightening of credit standards. A regression of the output gap on a distributed lag of the financial indicators is used to determine the index weights (Aykut, 2013). In the May 2009, FSI was constructed for Turkey comprising five sub-market indexes which are foreign exchange market pressure index, the riskiness of the banking sector, equity markets and perceptions of uncertainty towards this market (CBRT, 2009: 76-78).

Several other attempts have been made to develop a composite index for measuring financial stress. They include Illing and Liu (2006) who developed a financial stress index for the Canadian financial system. Using daily frequency covering the equity markets, bond markets,

foreign exchange markets as well as the banking sector, they aggregated the stress indicators into a single index by weighting the variables by the size of each market to which they pertain.
Hakkio and Keeton (2009) built a comprehensive index for financial stress in the U.S. economy known as the Kansas City Financial Stress Index (KCFSI). Using the principal component analysis alongside the equal-variance weighing method as well as using eleven indicators based on the representation of the features of financial distress, the study revealed that financial stress is the factor most responsible for the co-movement of the eleven variables.

Cardarelli et al., (2011) examined the impact of financial stress on economic activity, and the findings revealed that financial turmoil characterized by banking distress is more likely to result in severe downturns compared to stress mainly in securities or foreign exchange markets. Using the variance-equal weighing method, they construct a monthly FSI for 17 advanced economies. Building on the work of Cardarelli et al. (2011) and using the same methodology, Balakrishnan et al. (2011) developed FSIs for emerging economies. Also, Oet et al. (2011) developed a FSI for the United States called the Cleveland Financial Stress Index (CFSI). The CFSI was developed using daily data from 11 components reflecting four financial sectors namely: credit markets, equity markets, foreign exchange markets, and interbank markets. Most of the CFSI components are spreads (i.e. interbank liquidity spread, corporate bond spread, liquidity spread) and two of the remaining CFSI components are ratios, and one is a measure of stock market volatility.
Iachini and Nobili (2016) introduced an indicator for measuring systemic risk in the Italian financial market using portfolio aggregation theory method. This portfolio aggregation was used to capture the systemic dimension of liquidity stress. The result shows that the systemic liquidity risk indicator adequately captured extreme events that were characterized by high systemic risk.

Furthermore, Hollo et al., (2012) developed a Composite Indicator of Systemic Stress (CISS) with the application of basic portfolio theory to the aggregation of market specific sub-indexes. The portfolio-theoretic aggregation method takes into account the time-varying cross-correlations between the sub-indexes. The CISS measures stress in the financial system in the euro area. Using 15 individual stress measures to construct market specific sub-indexes, the study revealed that the CISS, compared with earlier FSIs, puts more weight on situations in which stress prevails in several markets at the same time. The idea behind the portfolio aggregation is that stress prevailing at several markets simultaneously is more systemic and dangerous for the economy as a whole. This is because financial instability is spread more widely across the financial system. Compared with earlier indexes, taking into account the correlation between market specific stress indicators, the CISS is more able to capture the concept of systemic stress.

Islami and Kurz-Kim (2013) also develop a composite FSI for the euro area. The authors base their FSI on its ability to predict developments in the real economy and select risk variables based on their correlation with economic activity, measured by industrial production.

In the case of emerging markets, Stolbov and Shchepeleva (2016) employed the PCA approach to calculate the FSI for emerging markets including Russia, China, India, Brazil, South Africa, Indonesia, Turkey, Mexico, Malaysia, Thailand, Philippines, Chile, Columbia as well as Peru. Using six variables, the results of the study show that the FSI for most emerging markets exhibited surge around September – October 2008 and this is assumed to have been caused by the emergence of the GFC (Stolbov and Shchepeleva, 2016). This section presents the calculation of FSI for emerging African economies such as Kenya, Egypt, Nigeria, and South Africa which is also known as the KENS economy. The FSI is calculated for the EAEs through four sub-indexes and calculated using monthly data.

In this study, following the study of Hollo et al. (2012) and Huotari (2015), a financial stress index for African emerging economies would be developed by aggregating individual stress indicators from four different markets namely: money market, bond market, equity market, and the foreign exchange market. There are different aggregation methods that have been used in literature such as the equal weighting method; correlation based weighing method, principal component analysis, market size weight etc. This study will employ the equal-variance; principal component analysis (Hollo et al. 2012) methods to develop a composite index for monitoring the financial system.

3.2 INDEX CONSTRUCTION PROCEDURES

The building of a financial stress indicator is not just only useful in monitoring stress but as well useful as an early warning signal (EWS) tool. However, a FSI will be useless in monitoring systemic risk if it is made up of noisy variables. In this study, I first used up to 18 indicators for the construction of the index but 5 of the indicators were dropped as it amount to noise in the process. Constructing FSIs involves a number of steps. First, the selection of the markets that were incorporated after which the indicators for each market segments were identified; secondly, the selected indicators were transformed. The third step is the aggregation of the transformed indicators into a composite index called FSI, while the final step is forecast accuracy evaluation (See Figure 3.1).

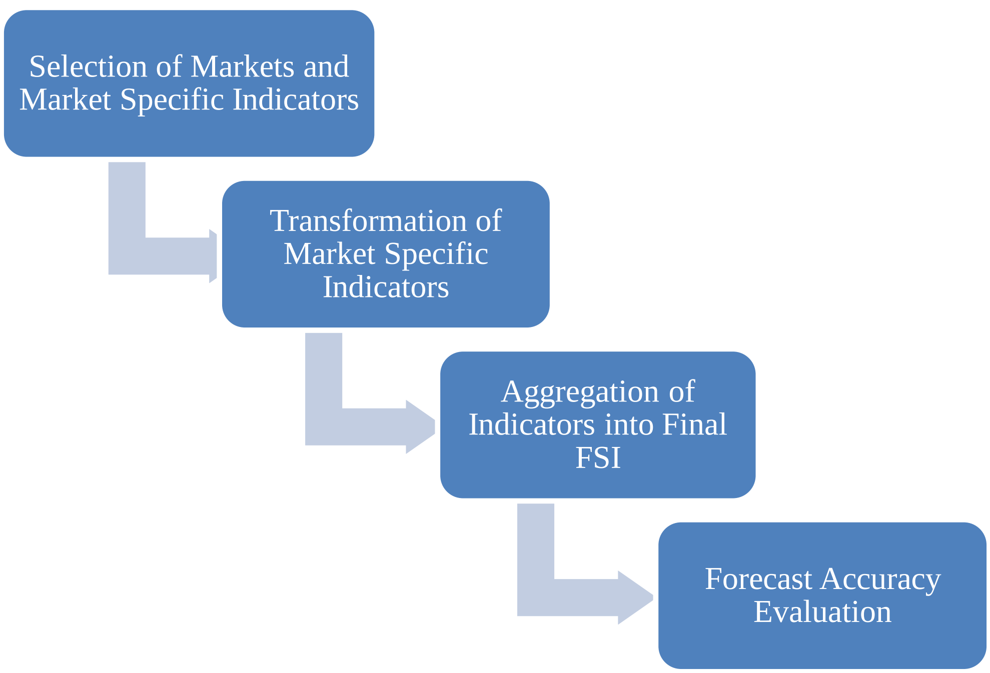


Figure 3. 1: Steps in Index Construction

Source: Author

There are a number of estimation techniques and they are briefly discussed in the next section. It must be noted that there is generally a trade-off while choosing the type of data to be included for the measurement of financial stress. This trade-off is with respect to the time span and the frequency of the data to be used. FSIs can either be constructed with time series data such as stock price, exchange rate, interest rate, corporate bonds and treasury bills which have a longer time span or with relatively new measures such as overnight rate, credit default swap spread etc. with shorter time span. Using longer time series data is advantageous in testing the predictive power and properties over several business cycles compared to data with a shorter time span, although this new measures might be advantageous in revealing prevailing market condition (). The second trade-off is the frequency to be used. High frequency (daily, weekly) date tends to facilitate better decision making to the extent that that shocks can be more quickly identified with weekly data than monthly data. However, some of the data to be used are not available on a daily or weekly basis.

3.2.1: Selection of Markets and Market Specific Indicators

As noted earlier, the FSI is useful in monitoring financial stress. However, FSI will be useless in monitoring systemic risk if it is made up of noisy variables[13]. When trying to classify a financial crisis, one essentially considers the level to which a number of variables deviate from some long- term trend. For example, when there is a misalignment in market A which causes abnormalities in values within market B (contagion), there will be a feedback effect which will make the selection of the appropriate stress variables a little be difficult as the researcher may concentrate on the response to propagation events rather than as the first rumblings of distress (Oet, et al. 2011). A useful framework for accomplishing this task considers two factors for each indicator: what is the precedent set by the indicator's value and how much does that precedent matter. Once the correct indicators have been selected, the next stage is to aggregate these indicators into a single FSI. As noted earlier, the FSI was constructed using monthly data from four different markets segment namely: money market, bond market, foreign exchange markets, as well as the equity markets. The indicators are explained in detail in the next section.

3.2.2.1 Money Market

In selecting indicators for the money market, each of the indicators must reflect liquidity and counterparty risk in the interbank market. The variables capture some features like flight-to-

[13] A key technical challenge to be overcome by an appropriate choice of the weighting methodology is the potential for false alarms. The potential for false alarms should be balanced against the possibility of missing important events by setting warning standards too high.

quality and flight-to-liquidity effects as well as the effects of adverse selection problem on banks during stress periods.

Realized volatility of the 3-month interbank rate, which is calculated as the monthly absolute rate of change. It is calculated as the square root of the monthly sum of squared daily log returns using the formulae:

$$rvol = \sqrt{\sum_{t=1}^{n} R_t^2} \tag{3.1}$$

where R is the monthly returns of the interbank rate, t is the trading day and n is the number of trading months. This is also used by Hollo et al. (2012 and Huotari (2015).

Interbank liquidity spread which is the spread between the 3-month interbank rate and 3-month Treasury bills. This represents a measure of liquidity and counterparty risk and the convenience premium on short term treasury papers.

$$\text{Interbank liquidity spread} = \text{3MIR} - \text{3Month Treasury Bill} \tag{3.2}$$

where 3MIR is the 3-month interbank rate and 3MTB is the 90-days Treasury bill market rate.

To capture banking stress and measure the anxiety or better still apprehension with which bank lend to one another, the three-month interbank rate – interest rate was used. This can be referred to as the interbank cost of borrowing. This indicates the risk premium that banks place on short term funds to lend one another.

$$\text{Interbank cost of borrowing} = \text{3MIR} - IR \tag{3.3}$$

where 3MIR is the 3-month interbank rate and IR is the policy rate. It can also be used as an indicator of counterparty risk.

3.2.2.2 Bond Market

Selecting indicator indicators for the bond market must reflect the solvency and liquidity condition in the bond market. This might be as a result of increased uncertainty or risk aversion of investors.

Realised volatility in the 10-year government bond index. This measure stress in the bond market

Yield spread between 10-year government bond index and US 10 year government index, ditto UK, and the Euro. This reflects the risks spread that investors require for investing in an African government bond.

The sovereign bond spread which is measured by the difference between the 10 Year government bond and the US 10 year government bond yield.

$$\text{Sovereign bond spread} = 10YBY - US10YBY \quad (3.4)$$

Where 10YBY is the 10 Year bond yield for the emerging African countries while US10YBY is the United State 10 Year bond yield.

3.2.2.3 Foreign exchange market

The foreign exchange market is very important because of its ability to reflect fluctuations in the financial market through the exchange rate as well as its impact of trade (import and export). The indicators selected in this segment reflect movement in the foreign exchange markets. Stress in the foreign exchange markets is measured by the volatility between country-specific currencies and three other major currencies, namely US dollars (USD), British Pounds (GBP) and the Euro (EUR). This was estimated using monthly averages of monthly log returns, transformed using empirical normalisation (Kocisova and Stavarek, 2015). It must be noted that increased volatility reflects uncertainty in the foreign exchange markets.

CMAX for ZAR, NGR, KYS and EGY to US dollars, GBP, and the EUR was used to measure the cumulative loss over the specific time frame.

$$CMAX_t = \frac{x_t}{Max[x \in (x_{t-j})j = 0,1,2,\dots,T]} \quad (3.5)$$

where x is the stock market index and the moving time window is determined by T (24 months). It must be noted that the CMAX compares the current value of the variable with its minimum values over sample T. This is advantageous because it makes any sharp decline in price more visible. The rolling maximum in the denominator was defined over a twenty-four (24) month period. ZAR is the South African rand, NGR is the Nigerian naira, KYS is the Kenyan shillings while EGY is the Egyptian pounds.

3.2.2.4 Equity Market

To capture stress in the equity market, the realised volatility of the total market equity was used. It is calculated as the monthly sum of the daily log returns of the all share index.

$$RALSI = \sqrt{\sum_{t=1}^{n} R_t^2} \tag{3.6}$$

Where $RALSI$ is the monthly log returns for the all share index.

The CMAX as explained earlier in Equation 5 for the all share index. This helps in measuring the maximum cumulated loss over the time period.

$$CMAX\ (ALSI)_t = \frac{x_t}{Max[x \in (x_{t-j}) j = 0,1,2,\ldots,T]} \tag{3.7}$$

3.2.3 Data and Transformation

Our FSI uses monthly observable financial markets' data to capture the continuity of stress in financial markets. The data is of high quality, sourced from the country-specific central banks; IMF-IFS, Bloomberg, and investing.com. It must be noted that although the researcher intends to start the analysis from 2000 and on a daily or at most weekly basis, some of the data were not available from the said date. Monthly data were used starting from January 2006 till December 2017. The data include 10 Year government bond for each of the countries, interbank rate, 3M TB, interest rate, All share index, exchange rate of each country currency against the US dollars, Pounds and Euros, US 10 Year bond yield, others would be used. For better comparison, the unit of measurement of the data is in US dollars.

In this study, four market Categories (Money, bond, equity, and foreign exchange). This is followed by the selection of market specific stress indicators to be included in the index. Transformation of market specific stress indicators was carried out using the empirical normalisation (Kocisova and Stavarek, 2015). Through this process, all indicators were transformed into the same scale of between zero and one (0, 1). The formula is presented in Equation 3.8:

$$z_{ij} = \frac{x_{ij} - min_j[x_{ij}]}{max_j[x_{ij}] - min_j[x_{ij}]]} \tag{3.8}$$

where x_{ij} is the jth value of the ith component of FSI. This is done by subtracting the minimum value of the sample variable from each variable i and then dividing it by its range. The final step is the aggregation of these indicators into the final FSI.

3.2.3 Estimation Technique Aggregation

After collecting the data for FSI, the next stage is to aggregate the collected data into one measure. The index is very useful in capturing co-movement of risk in a broad array of data across the different sectors within the macroeconomic space. While aggregating the data into one measure, it is important to covert the data into a common unit of measurement for better comparison (Normalization). This helps to normalize fluctuations across variables and ensure that they are on the same scale. The methods include standardization (standardization include studying the difference in a variable's level relative to an average from a reference period), cumulative density function (CDF), mean/variance method among others (Nelson & Perli, 2007; Cardarelli, Elekdag, and Lall, 2011). The mean/variance is carried out by subtracting each data's historical (sample) mean and dividing by its standard deviation. Also, while constructing the index, the variables can as well be grouped into sub-indexes based on volatility or co-movement of related variables.

3.2.3.1 Construction of Sub-indices

The thirteen indicators used in this study are grouped into four market segment (Money, bond, equity, foreign exchange and real estate). Each of the raw indicators captures information about the stress level within each market segment. The market segment sub-indices were calculated based on a simple arithmetic average. This implies that each of the raw risk indicators is given equal weight in the sub-index. The sub-indexes are then aggregated into the final index referred to as FSI. There are a number of aggregation methods and they include equal weighing method (EWM), principal component analysis (PCA), regression-based weighing method and portfolio aggregation method among others. In the VEW method, the indicators (sub-indexes) are averaged together to produce a final measure (Cardarelli, Elekdag, and Lall, 2011). With respect to the PCA, a common component which is assumed to capture the stress is extracted among many variables. In order words, the PCA assumes that each of the variables used to construct the FSI captures some aspect of financial stress. This factor, which is the first PC, becomes the FSI. They are discussed in details in the next section.

3.2.3.2 Variance Equal Weight (VEW)

The variance equal weight is the most frequently used stress index aggregation method. The method is the most straightforward and perhaps the most intuitive weighing method (Huotari, 2015). In this method, the distance of each index from its mean is calculated. This ensures that each component in the index is given equal importance.

$$FSI_t = \sum_{i=1}^{k} \frac{X_{i,t} - \bar{X}_i}{\sigma_i} \qquad (3.9)$$

Where k is the number of variables combined in the index, $\bar{X}_i$ is the sample mean of the variable X_i and σ_i is the sample standard deviation of the variableX_i. These variables are assumed to be normally distributed. One major limitation of this method is that it fails to incorporate the correlation/co-movement between different stress indicators (Huotari, 2015).

3.2.3.3 Principal Component Analysis (PCA)

The PCA is a statistical technique that was developed by Pearson (1901) and Hotelling (1933) to simplify a data set (See Cambon and Estevez, 2016). It was noted earlier that the variance equal weight approach does not incorporate possible co-movement between stress indicators. However, since financial stress is more pronounced when there is the prevalence of stress in several markets simultaneously (Hollo et al. 2012), therefore a method that will take into account this systemic aspect of stress might likely produce a better result. One of such methods is the principal component analysis. The principal component analysis is widely used to generate a small number of artificial uncorrelated variables (which are linear combinations of the initial variables) accounting for most of the variance of the initial multidimensional dataset, thereby arriving at condensed data representation with minimal loss of information (Sinenko et al., 2013). According to Huotari (2015:25) "financial stress is assumed to be the factor most responsible for the co-movement of the market-specific variables, identified by principal components". The main aim is to capture the structural movements in a group of financial indicators. Although the PCA method is more complicated and suffers from reclassification problem, it takes into account co-movement between stress indicators.

3.2.4. Forecast Accuracy Evaluation

In this section the forecasting ability of the FSI. The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Theils Inequality Coefficient (TIC), Thiel U^2 Coefficient, Symmetric MAPE among others were used and they are defined as follows.

The Root Mean Square Error (RMSE) is defined as follows:

$$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t^s - Y_t^a)^2} \tag{3.10}$$

where Y_t^s is the forecasted value of the series, Y_t^a is the actual value and n is the number of periods of the forecast. The major limitation of the RMSE when used as a means to forecast evaluation is that it is only advantageous when comparing models, that is, it is not reflective of how accurate a model really is because it does not have an upper bound.

A more advantageous measure to evaluate the predictive accuracy of a model is Theil's inequality coefficient (TIC) (Pindyck and Rubinfeld, 1998). The TIC measures the root mean square error in relative terms. There are two Theil's coefficient named U and U^2 and they are defined as

$$U = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t^s - Y_t^a)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t^s)^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t^a)^2}} \tag{3.11}$$

The denominator imposes an upper bound to the U coefficient, which is bounded above by 1 and bounded below by 0, that is, $0 \leq U \leq 1$. This is particularly useful since it gives a threshold to evaluate the accuracy of a model and not only compare it to other models. The closer to 0 the coefficient is, the more accurate the model is.

$$U^2 = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t^s - Y_t^a)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t^a)^2}} \qquad (3.12)$$

The Theil's coefficient U^2 is not compared to U.

The U coefficient can be decomposed into three proportions that provide useful additional information on the performance of the model.

Bias,

$$U^M = \frac{(\overline{Y}^s - \overline{Y}^a)^2}{\frac{1}{n}\sum_{t=1}^{n}(Y_t^s - Y_t^a)^2} \qquad (3.13)$$

Variance,

$$U^S = \frac{(\sigma_s - \sigma_a)^2}{\frac{1}{n}\sum_{t=1}^{n}(Y_t^s - Y_t^a)^2} \qquad (3.14)$$

Covariance,

$$U^C = \frac{2(1-\rho)\sigma_s\sigma_a}{\frac{1}{n}\sum_{t=1}^{n}(Y_t^s - Y_t^a)^2} \qquad (3.15)$$

The bias proportion measures the systematic error of the forecast; it gathers the share of the simulation error that comes from bias, that is, the difference between the averages of the forecasted series and the actual series. The variance proportion is intended to provide a measure of how well our forecast replicates the volatility of the actual series. The covariance proportion offers a measure of the unsystematic error in the forecast. The ideal distribution of proportions for any non-zero inequality coefficient would be $U^M=U^S=0$ and $U^C=1$. The results for these proportions are also included.

3.3 ESTIMATION RESULTS

This section is dedicated to present the result of the indexed constructed. The section is divided into 5 subsections. Subsection 1 gives estimation result for South Africa followed by that of

Egypt in Subsection 2. The estimation result for Kenya and Nigeria are presented in Subsection 3 and 4 respectively, while that of emerging African economies is presented in Subsection 5.

3.3.1 Financial Stress Index for the South African Economy

The FSIs constructed for the South African financial system using the variance-equal weighing (VEW) method as well as the PCA and the results are presented in this sub-section. FSIs are tested based on their capacity to reveal previously well known periods of stress within the economy.

3.3.1.1 Descriptive Statistics

The descriptive statistics are presented in Table 3.1**.** All the indicators were standardized to a value between 0 and 1 using the empirical normalization method.

Table 3. 1: Descriptive Statistics for the South Africa Financial Sector

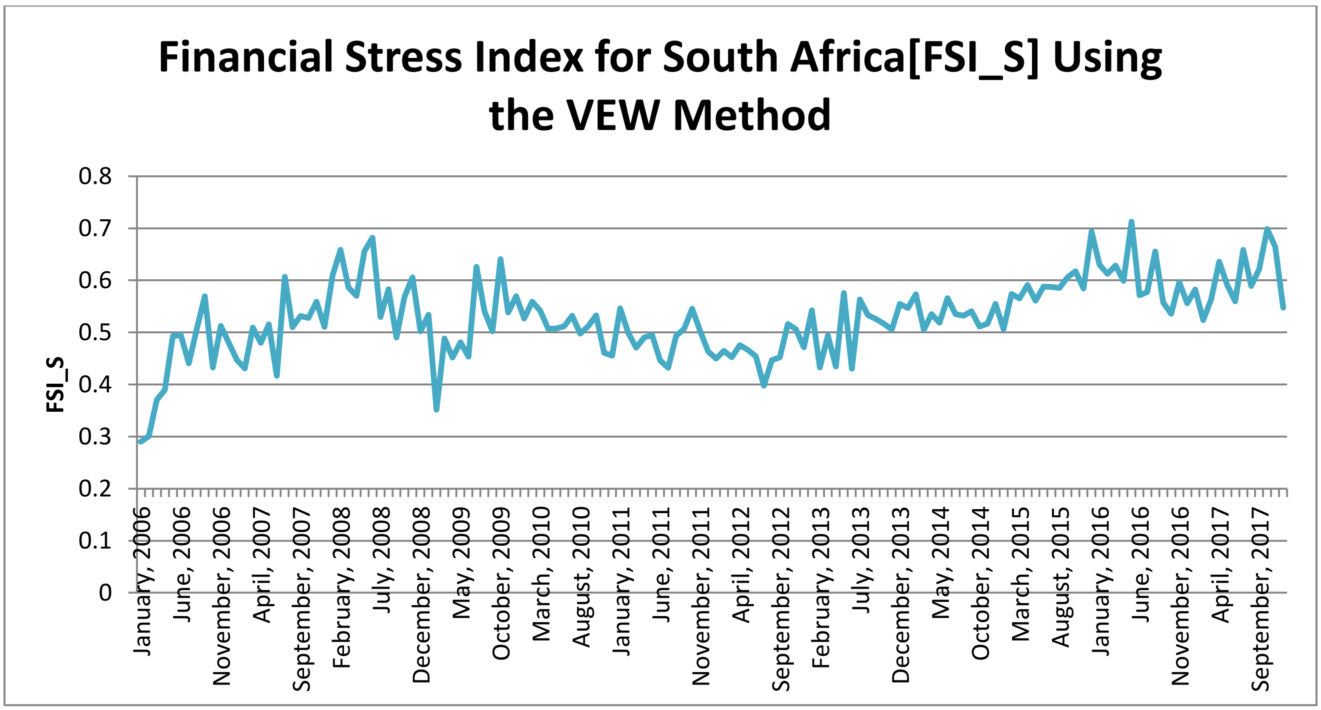
Variable	Obs	Mean	Std. Dev.	Min	Max
srvi	144	.6657349	.1434522	0	1
sils	144	.1807931	.1372663	0	1
sicb	144	.7381993	.1016174	0	1
srvb	144	.3694667	.1293575	0	1
ssbs	144	.583882	.2106923	0	1
srvu	144	.4427396	.1601912	0	1
srvg	144	.5309465	.1532399	0	1
srve	144	.510652	.1595205	0	1
scmu	144	.493765	.2938971	0	1
scmg	144	.5777624	.2632836	0	1
scme	144	.5918454	.2400568	0	1
srva	144	.5925379	.1578984	0	1
scma	144	.5820815	.2396547	0	1
smm	144	-6.52e-09	1.000002	-7.264512	2.576354
sbm	144	-1.91e-08	1	-2.771255	1.975004
sfm	144	2.29e-08	1.000002	-2.465442	1.700248
sem	144	-2.47e-08	1	-2.428834	1.743836
FSI_S	144	-2.99e-09	1.000003	-2.428838	1.743845

Source: Estimation

The descriptive statistics of the variables are given in Table 3.1.

3.3.1.2 Variance-Equal Weighting (VEW) Method

The result of the FSI using the VEW method is presented in Figure 3.2. This is the most common method used in estimating FSI in previous studies. Apart from that, it is easy to construct and interpret compared to other weighing methods. As noted earlier, all the indicators in each market segment were transformed using the empirical standardization method after they are aggregated using the arithmetic mean to derive each market segment sub-indices. The final FSI was then constructed using the arithmetic average of the four sub-indexes. Thus, the index values can be interpreted as the number of standard deviations from the sample mean.



Source: Estimation

Figure 3. 2: Financial Stress Index for South Africa Using VEW Method

The result as presented in Figure 3.2 revealed the extreme stress event occasioned by the global financial crisis and more of the domestic crisis ranging from labour crisis, energy crisis, political uncertainty among others which started in late 2015 and going into 2016.

3.3.1.3 Principal Component Analysis (PCA) Method

Due to the limitation, the VEW method noted earlier, the FSI was also constructed using the PCA and presented in Figure 3.3. Several other studies (Illing and Liu, 2006; Hakkio and Keeton, 2009; Sinenko, Titarenko, and Arins, 2013; Huotari, 2015) have also employed this method in the construction of FSI. Table 3.2 presents the eigenvalue and the proportion of the five principal components captured within the market segment sub-indices. The first principal component (PC) captures the larger proportion of the total variation within the stress indicators. As can be seen in Table 3.2, the first PC captures 48 percent of the total variation within the indicators. Logically, the more PC that is used for the FSI, the more the total variation that can be captured in the index. Nevertheless, adding more PC to the index also adds noise which makes it difficult to identify crisis periods. Therefore, the first PC is used to estimate the FSI_S.

Table 3. 2: Eigenvalue and Proportion of each Component in the PCA

Components	Eigenvalue	Proportion	Cumulative
Component 1	1.91296	0.4782	0.4782
Component 2	1.23195	0.3080	0.7862
Component 3	0.500228	0.1251	0.9113
Component 4	0.354856	0.0887	1.0000

Source: Estimation

The coefficient for all the market segment indicators are positive and they represent a one standard deviation change in the respective market segments from the final FSI due to the fact that all the indicators are standardized. The coefficients range from a low of 0.43 for the equity market segment to 0.53 for the foreign exchange market segment. The margin is quite small and this implies that all the market affects the FSI_S by almost the same proportion, although the foreign exchange market contributes more to the final FSI (Table 3.3).

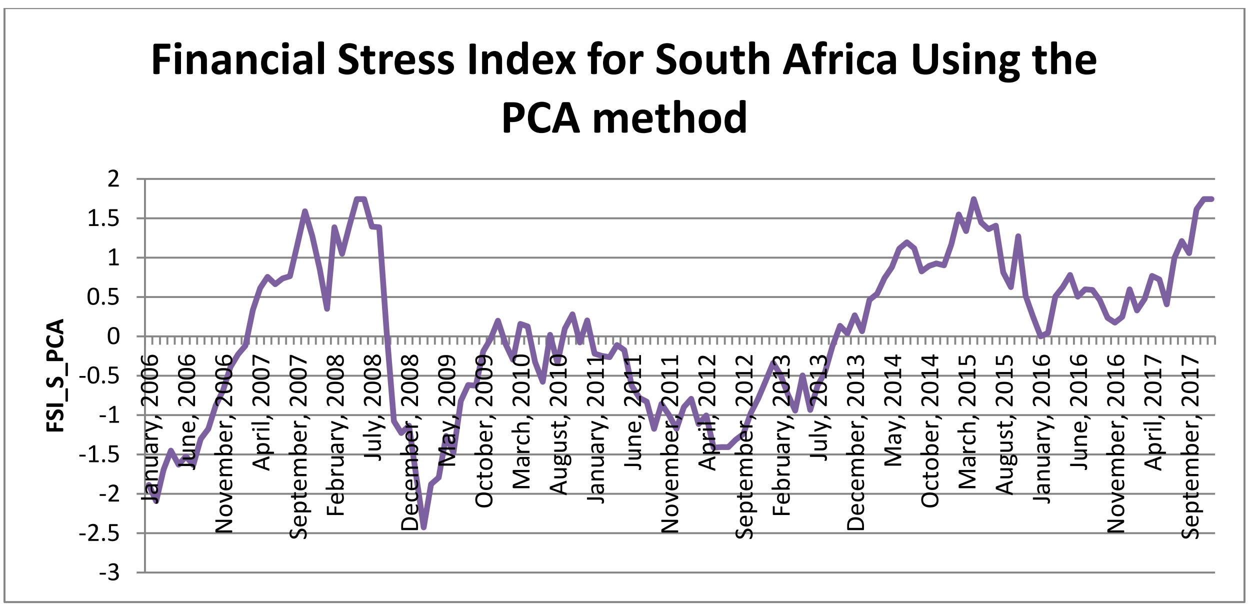
Table 3. 3: Coefficient for all Market Segments

Market segment	**Composed 1**
Money market	0.5044
Bond market	0.5163
Equity market	0.4350
Foreign exchange market	0.5383

Source: Estimation

3.3.1.4 Identification of Stress Events

The FSI_S reflect dynamics in the surge in tension within the financial system. As noted earlier, the stress indicators were standardized to a value between 0 and 1. This implies that 0 which is the mean of the FSI_S would mean that the financial system is experiencing an average risk level. This is therefore adopted as the threshold level above which would mean extreme or a signal of impending crisis. The results as presented in Figure 3.3 revealed previous well known financial crisis. The well-known global financial crisis, which began in 2007 as well as the sovereign debt crisis had some impact on the South African financial system.



Source: Estimation

Figure 3. 3: Financial Stress Index for South Africa Using the PCA Method

The impact of the sub-prime mortgage crisis was then quickly shown to have implications beyond the US. The FSI_S first signalled an extreme level of stress around August 2007 this was the time that BNP Paribas suspended three investment funds that invested in asset-backed securities linked to the subprime mortgage debts which had become totally illiquid. There were other events that happened which led to a rise in the FSI_S which reached the maximum (1.74) around May/June 2008. At this time, global exports were down by 22 percent, Bear Stearns in the US collapsed (Tooze, 2018). By April 2008 the US Treasury and US Federal Reserve Bank had to bail out two financial institutions as the ‘credit freeze’ gripped their financial system. Like a pack of dominoes, most banks with large sub-prime exposures joined the solvency and liquidity scuffle.

As liquidity issues became more challenging, investors began to withdraw funds from emerging markets in a so-called flight to quality as risk aversion set in. In South Africa, the Johannesburg Securities Exchange all-share index fell from a high of 32, 542 on 23 May 2008 to a low of 18066 on 21 November 2008, but volatility and uncertainty in the market were as worrying as the absolute fall. New listings remained subdued throughout 2009. However, the all-share index has since picked up, and it stood at 27 895 as of 5 January 2010 (Padayachee, 2012). The situation remained above the threshold level almost all through 2008 after which there was a steady decline around February 2009. Based on the result, we also observed a mild increase in stress that is above the threshold of 0 in late 2010 (m4). It later rose 2014m6 and reaching another peak in 2015 (m4) as well as towards the end of the sample. For the latter part of the FSI_S, domestic factors such as political uncertainty (Ousting of former president Jacob Zuma in December 2017).

3.3.1.5 Forecast Accuracy Evaluation

In this section, the forecasting ability of the FSI_KD is tested against the Financial Condition Index for South Africa (FCI_S_KM) developed by Kabundi and Mbelu (2017). The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Theils Inequality Coefficient (TIC), Thiel U^2 Coefficient, Symmetric MAPE among others were used and the result is presented in Table 3.4. For all the models forecasting, the in-sample estimation was from 2006m01 to 2011m12, while the out-of-sample forecast was from 2012m01 to 2017m12 (See Appendix for detailed result). All the variables passed the necessary diagnostic test. The forecast was made using the dynamic model.

Table 3. 4: Forecast model evaluation

	RMSE	MAE	MAPE	Theil	Theil U^2	Bias	Variance	Covariance	SMAPE
FSI_S_KM	0.9658	0.8579	256.1437	0.9130	20.7909	0.7890	0.1360	0.0749	183.9383
FSI_S_KD	0.8835	0.6765	283.8550	0.5900	3.3148	0.3050	0.0954	0.5992	114.9979

RMSE: Root Mean Square Error; MAE: Mean Absolute Error; MAPE: Mean Absolute Percentage Error; Theil: Theil inequality coefficient; Theil U^2 Coefficient; Bias, variance and covariance are the decomposed proportion of the Theil's Inequality coefficient

Source: Estimation

From the result as presented in Table 3.4, it is clear that the FSI_S_KD performs better than the FCI_S_KM developed by Kabundi and Mbelu (2017). This is because the RMSE (0.8835), MAE (0.6765), Theil's U coefficient (0.5900), U^2 (3.3148) and SMAPE (114.9979) of the FSI_S_KD model were lower than that of FCI_S_KBD (See Table 3.4). The same goes to that bias, variance and covariance decomposition of the Theil's coefficient. In Figure 3.4, the FSI for South Africa using PCA aggregation method is plotted against the FCI proposed by Kabundi and Mbelu (2017) is presented. In all, both indexes captured the global financial crisis that started in 2007, however, the FCI_S_KM did not capture more of the domestic crisis that rocked the country from late 2015 onward.

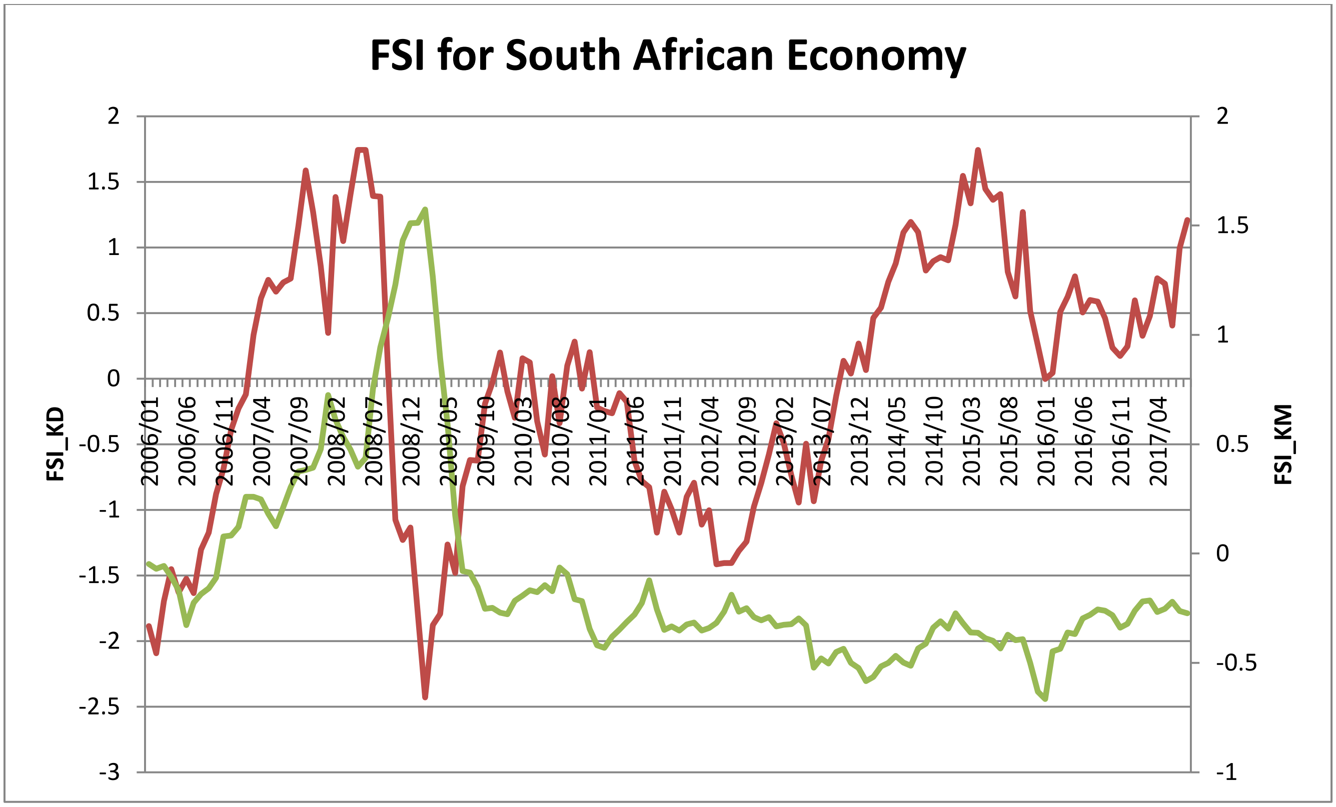


Figure 3. 4: FSI for South Africa using the PCA and the FCI constructed by Kabundi and Mbelu (2017)

Source: Estimation

The result as presented in Figure 3.4 show that both domestic and international shocks created uncertainty in the South African financial system. On the international scene, we have the financial crisis while on the domestic scene; we have slow growth, labour crisis, and energy crisis, coupled with political uncertainty.

3.3.2 Financial Stress Index for the Egyptian Economy

The financial stress index for the Egyptian financial system is developed and presented in this sub-section. The FSI was constructed using the VEW and PCA method. The descriptive statistics are presented after which the result of the estimation based on the two methods.

3.3.2.1 Descriptive Statistics

Table 3. 5: Descriptive Statistics for the Egyptian Financial Sector

Variable	Obs	Mean	Std. Dev.	Min	Max
ervi	144	.3790951	.1246507	0	1
eils	144	.5484414	.1881705	0	1
eicb	144	.5020586	.1592384	0	1
ervb	144	.4863215	.1378351	0	1
esbs	144	.5304592	.2890187	0	1
ervu	144	.1765463	.0720921	0	1
ervg	144	.227001	.0774769	0	1
erve	144	.1927302	.0761621	0	1
ecmu	144	.7653961	.3277336	0	1
ecmg	144	.7209127	.2887542	0	1
ecme	144	.7132819	.2879668	0	1
erva	144	.5904209	.1344285	0	1
ecma	144	.5818192	.2916674	0	1
emm	144	-2.05e-10	1.000009	-2.914637	2.399743
ebm	144	1.75e-08	1	-1.83538	1.624604
efm	144	1.46e-08	1.000001	-2.335424	.7158385
eem	144	-4.91e-08	1	-1.994804	1.433759
FSI_E	144	1.53e-09	1.000001	-1.994805	1.433764

Source: Estimation

The result as presented in table 3.5 show that the values of the indicators ranged between 0 and 1.

3.3.2.2 Variance-Equal Weighting (VEW) Method

The result of the FSI using the VEW method is presented in Figure 3.5 as noted earlier, this is the most common method used in estimating FSI in previous studies due to its simplicity when constructing and interpreting. All procedures used in 3.2.1.2 were followed. Thus, the index values can be interpreted as the number of standard deviations from the sample mean.

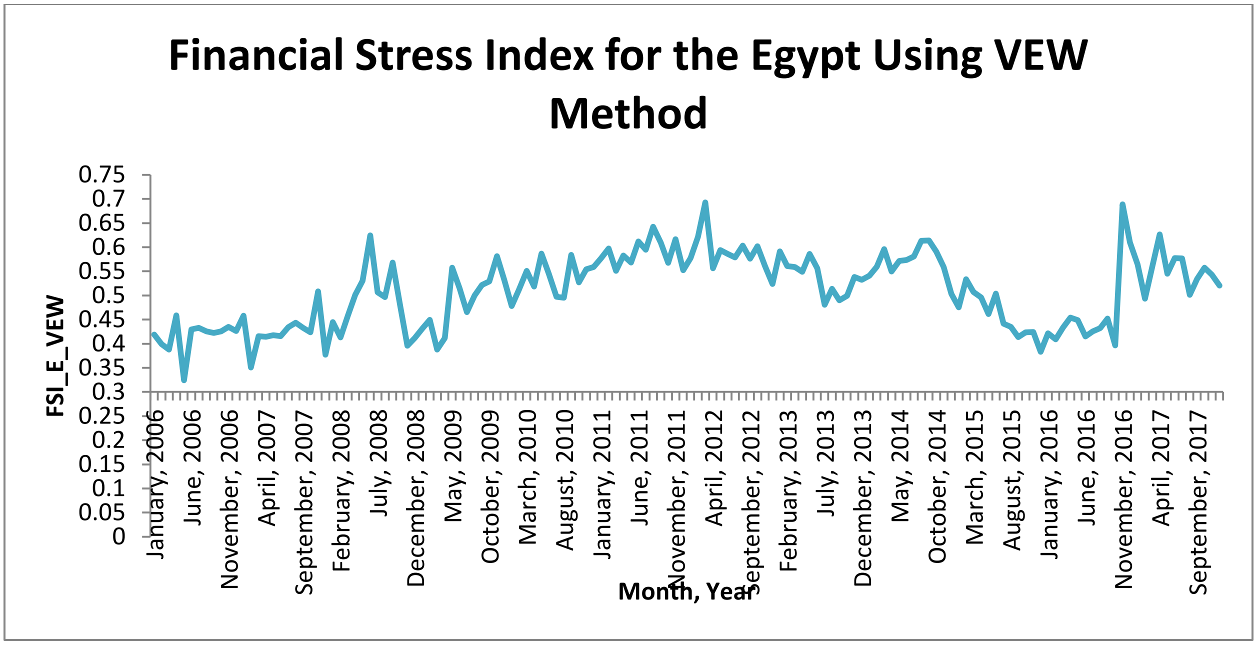


Figure 3. 5: Financial Stress Index for Egypt Using the VEW Method

Source: Estimation

The result of the FSI_E as presented in Figure 3.6 revealed that the GFCs which started around 2007 was not as pronounced on the Egyptian financial system, although it affected the economy. This was also supported by the study of Ibrahim (2012) who found that the crisis was more pronounced on the real economy other than the financial sector due to series of banking sector reforms carried out at that time and as well the limited level of integration of the Egyptian financial system to the global financial market. The FSI_E reached its maximum in 2016m11 which coincided to the time that the free float exchange rate was announced. During this period, the Egyptian pound lost its value by almost 50 percent.

3.3.2.3 Principal Component Analysis (PCA) Method

The eigenvalue and the proportion of the four principal components captured within the market segment sub-indices are presented in Table 3.6. The first principal component captures the larger proportion of the total variation within the stress indicators. As can be seen in Table 3.6, the first PC captures 48 percent of the total variation within the indicators. Nevertheless, adding more PC to the index also adds noise which makes it difficult to identify crisis periods. Therefore, the first PC is used to estimate the FSI_E.

Table 3. 6: Eigenvalue and Proportion of each Component in the PCA

Components	**Eigenvalue**	**Proportion**	**Cumulative**
Component 1	2.23097	0.5577	0.5577
Component 2	0.93410	0.2335	0.7913
Component 3	0.63097	0.1577	0.9490
Component 4	0.20390	0.0510	1.0000

Source: Estimation

The coefficients for all the market segment indicators obtained from the PCA are given in Table 3.7. Based on the signs of the coefficient, only the money market and bond markets are positive, this means that they act to raise financial stress in Egypt. On the other hand, the foreign exchange market and equity market is negative, which means they do not contribute to financial stress in Egypt. These coefficients represent a one standard deviation change in the respective market segments on the final FSI due to the fact that all the indicators are standardized. The coefficients range from a low of -0.49 for the foreign exchange market segment to 0.60 for the bond market segment (Table 3.7).

Table 3. 7: Coefficient for all Market Segments

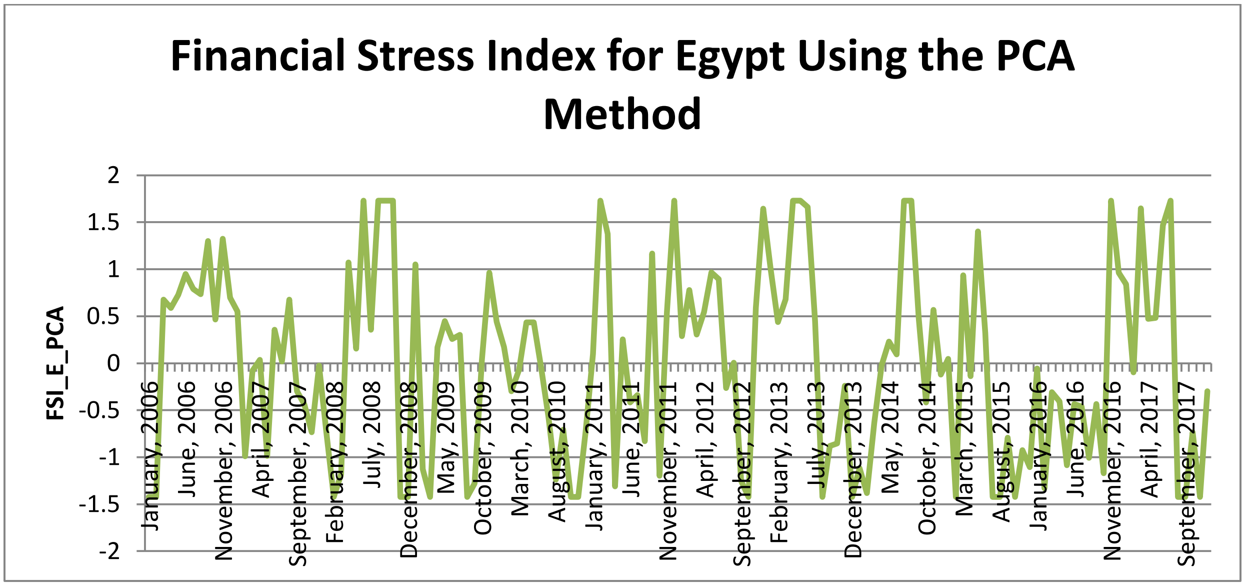
Market segment	**Composed 1**
Money market	0.5639
Bond market	0.6030
Foreign exchange market	-0.4921
Equity market	-0.2761

Source: Estimation

3.3.2.4 Identification of Stress Events

The FSI_E reflect dynamics in the surge in tension within the Egypt financial system. All the procedures used in Section 3.2.1.4 were applied as well. The results as presented in Figure 3.6 revealed that the index was above the threshold for most of the period under consideration. The

Egyptian financial system had been experiencing a series of financial turmoil together with political and other domestic crisis. The well-known global financial crisis, which began in 2007 as well as the sovereign debt crisis, the Euro area crisis had some impact on the Egyptian financial system.



Source: Estimation

Figure 3. 6: Financial Stress Index for Egypt

The FSI reached the maximum (1.73) during the financial crisis and the collapse of Lehman brothers in 2008m8, that is when Lehman Brothers filed for bankruptcy protection and AIG was rescued to avoid bankruptcy. During this period, the financial crisis affected the Egyptian economy in many respect. The economy slowed down and trade was also affected since about 32 percent of Egyptian export goes to the United States while 32.5 percent of its import from the United States and European Union (Ibrahim, 2012). The GDP growth rate which was around 7.2 percent in 2007/08 fell to 4 percent in 2008/09 (Ibrahim, 2012). Foreign direct investment and remittances also declined. In addition to that, the Egyptian stock exchange collapsed due to the collapse of the foreign stock markets as foreign investors hasten to sell off their shares in the Egyptian stock market to cover their vulnerable financial position, especially following their losses elsewhere. Moreover, most Egyptian big corporations are listed in foreign markets particularly those of London and New York - thus their shares declined with the collapse that hit these markets. The fact that seventy per cent of investors in the Egyptian stock exchange are small shareholders, compounds the crisis because they hurried to sell their shares even when prices fell to the level of 20 per cent (Ibrahim, 2012). The Cairo index and Alexandria Stock Exchanges (CASE) made harsh losses as it fell from 2727.7 points in August 2008 to 1556.7 points in November 2008, while, the Case30 on the average fell from 8449.6 points in August 2008 to 4205.9 points in November 2008 and by January 2009, it has fallen to 3780.30 points (Ibrahim, 2012). Based on the result, we also observed several peaks in the FSI_E. They include 2011m2, 2011m09, 2011m12, 2012m12, 2013m04, 2014m07, 2015m05, 2016m11, 2017m03 and 2017m06. These coincided with major extreme cases of shock in the Egyptian financial system. For example, the 2006m11 peak coincided with the currency crisis occasioned by the announcement of a free float exchange rate, which made the Egyptian pounds to shed about 50 percent of its value.

3.3.3 Financial Stress Index for the Kenyan Economy

The FSIs constructed for the Kenyan financial system are presented in this section using the variance-equal weighing (VEW) method as well as the PCA. The FSIs are tested based on their capacity to reveal previously well known periods of stress within the economy. The descriptive statistics are presented in Table 3.8.

3.3.3.1 Descriptive statistics

Table 3. 8: **Descriptive Statistics for the Kenyan Financial Sector**

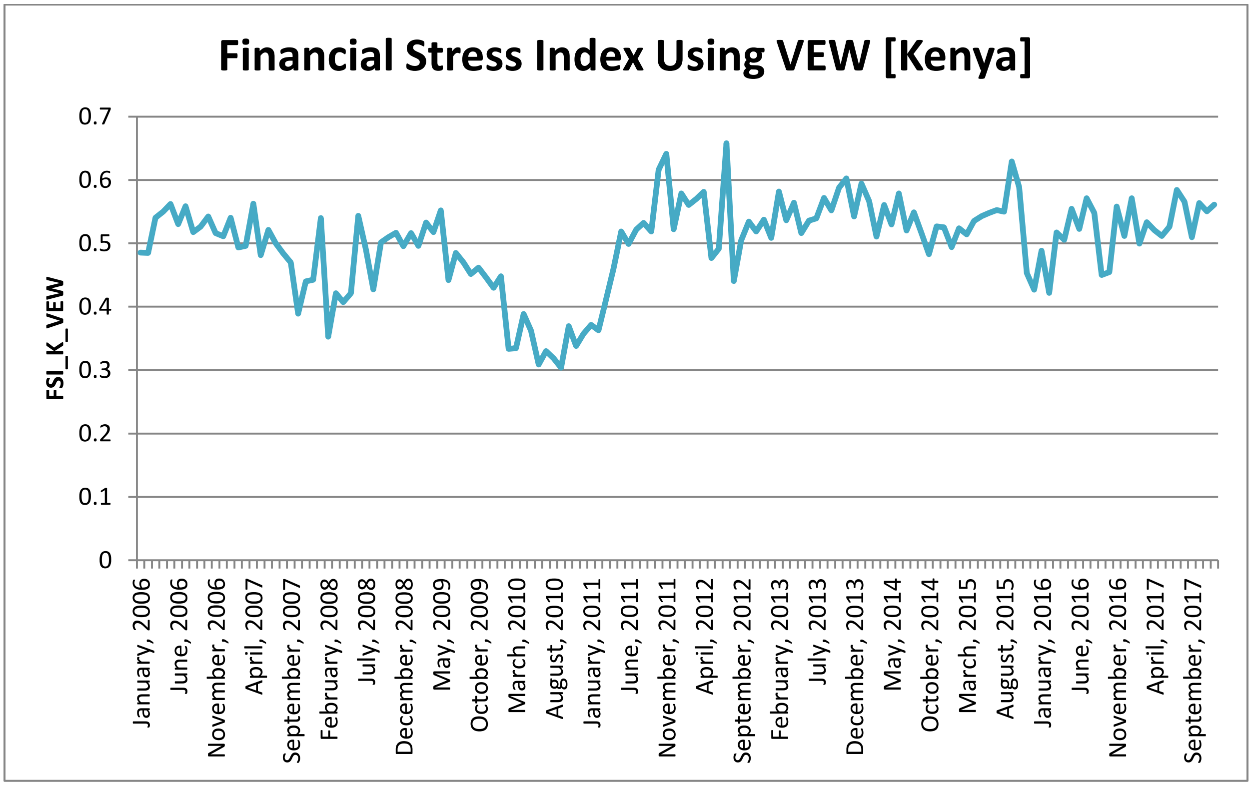
Variable	Obs	Mean	Std. Dev.	Min	Max
krvi	144	.3974035	.125771	0	1
kils	144	.3627396	.1441591	0	1
kicb	144	.3458208	.1383421	0	1
krvb	144	.5683983	.1034521	0	1
ksbs	144	.5033519	.2167955	0	1
krvu	144	.4931377	.1106756	0	1
krvg	144	.5315131	.1281203	0	1
krve	144	.511373	.1280114	0	1
kcmu	144	.51832	.2894825	0	1
kcmg	144	.661503	.2416384	0	1
kcme	144	.6123502	.2242481	0	1
krva	144	.5944829	.1373144	0	1
kcma	144	.5011549	.241005	0	1
kmm	144	1.29e-08	1.00001	-2.516301	4.420621
kbm	144	-1.90e-08	1	-2.321783	2.29086
kfm	144	1.90e-08	1.000001	-3.994761	3.817069
kem	144	-4.99e-09	1	-4.329358	2.953202
FSI_K_PCA	144	7.58e-10	1.000001	-3.994772	3.817068

Source: Estimation

In general, the variables were selected based on international literature, previous study, and systemic relevance of the variables in the Kenyan financial system and availability (Table 3.8).

3.3.3.2 Variance-Equal Weighting (VEW) Method

The result of the FSI for the Kenyan financial market using the VEW method is presented in Figure 3.7 as noted earlier, this is the most common method used in estimating FSI in previous studies due to its simplicity when constructing and interpreting. All procedures used in 3.2.1.2 were followed. Thus, the index values can be interpreted as the number of standard deviations from the sample mean.



Source: Estimation

Figure 3. 7: FSI using Variance-Equal Weighting (VEW) Method

The result of the FSI for Kenya using the VEW method presented in Figure 3.7 revealed some extreme cases of stress in the Kenyan financial system. However, this did not capture the entire historical extreme crisis. Although it could reveal some cases of extreme events during the second half of 2011 as well as the first half of 2012, it didn't pick the more severe GFC.

3.3.3.3 Principal Component Analysis (PCA) Method

As stated in Section 3.2.1.3 that due to the limitation the VEW method noted earlier, the FSI for the Kenyan financial system was also constructed using the PCA and presented in Figure 3.8. Table 3.9 presents the eigenvalue and the proportion of the four principal components captured within the market segment sub-indices. The first principal component captures the larger proportion of the total variation within the stress indicators. As can be seen in Table 3.9, the first PC captures 31 percent of the total variation within the indicators. The result showed that the first two principal components, extracted from the indicators, jointly account for 59 percent of the variation within the stress indicators.

Table 3. 9: Eigenvalue and Proportion of each Component in the PCA

Components	Eigenvalue	Proportion	Cumulative
Component 1	1.24300	0.3108	0.3108
Component 2	1.13002	0.2825	0.5933
Component 3	0.904151	0.2260	0.8193
Component 4	0.722827	0.1807	1.0000

Source: Estimation

The coefficient for all the market segment indicators is positive except that of the equity market and they represent a one standard deviation change in the respective market segments due to the fact that all the indicators are standardized. The coefficients range from a low of -0.5498 for the foreign exchange market segment to 0.6016 for the bond market segment. The margin is quite large and this implies that a unit standard deviation in the bond market has an effect on the FSI_K_PCA more than the other market segment (Table 3.10).

Table 3. 10: Coefficient for all Market Segments

Market segment	Composed 1
Money market	0.4126
Bond market	0.6016
Foreign exchange market	-0.5498
Equity market	0.4069

Source: Estimation

3.3.3.4 Identification of Stress Events

The FSI_K_PCA reflect dynamics in the surge in tension within the financial system. The results as presented in Figure 3 revealed previous well known financial crisis. The well-known global financial crisis, which began in 2007, sovereign debt crisis coupled with other domestic factors had some impact on the Kenyan financial system.

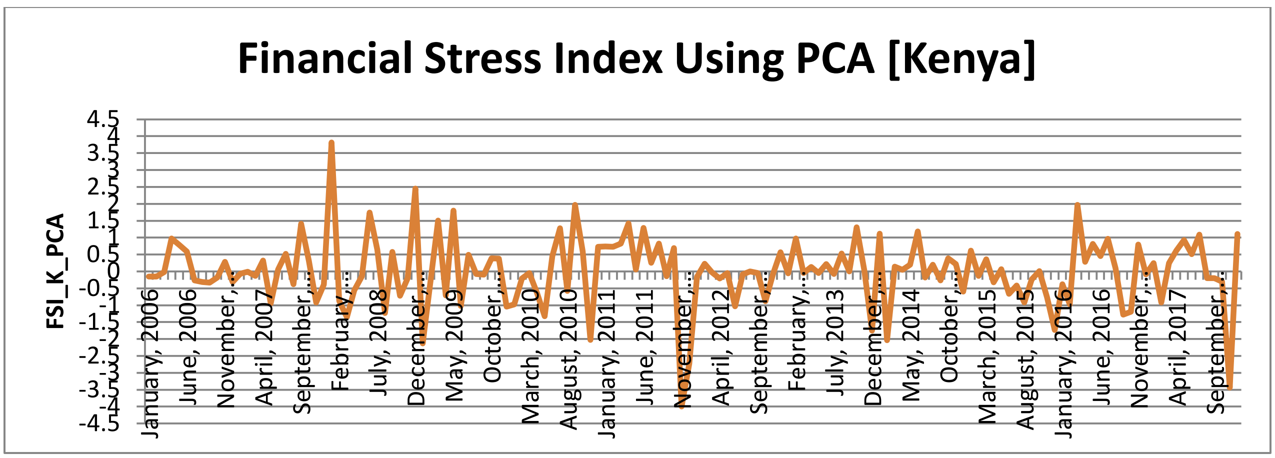


Figure 3. 8: FSI using Principal Component Analysis (PCA) Method

Source: Estimation

Based on the result as presented in Figure 3.8, the most extreme period of stress occurred in 2008, although some mild increase was observed in late 2010 till the first half of 2011 as well as the first half of 2016. The Kenyan real economy was badly hit by the global financial crisis as well as other domestic factors such the post-election violence. The economic impact of the politically instigated domestic crisis was immediately felt in the key economic sectors that drive the economy, particularly agriculture (which contributes 24 percent of the country's GDP), tourism and manufacturing. Prior to the post-election violence, the economy has been experiencing steady growth with real GDP growth rate rising from 5.1 percent in 2004 to 7.1 percent in 2007 with greater prospect of a better future, however as a result of the crisis, the real GDP growth rate which was 7.5 percent during the first quarter of 2007 declined to a negative growth rate of 1 percent in the first quarter of 2008 (Mwega, 2010; Were and Tiriongo, 2012).

Also in 2008, the Kenyan shillings depreciated against the major foreign currencies, for example, it depreciated against the US dollars by 15.6 percent, that is from an average of Ksh. 63.30 in December 2007 to Ksh 70.62 per US dollar in 2008 (Mwega, 2010; Were and Tiriongo, 2012). The inflation rate rose from 5.7 percent in December 2007 to a peak of 18.6 percent in May 2008 (). The emergence of the GFC reinforced the negative effects of the domestic crisis. The reflected in the decline in the stock market and volatility in the foreign exchange market (Were and Tiriongo, 2012). For example, the NSE-20 share index fell significantly (35 percent) in 2008 and also by 7.5 percent in January 2009 (Mwega, 2010).

3.3.4 Financial Stress Index for the Nigerian Economy

The financial stress index for the Nigerian financial system is developed and presented in this section. The FSI was constructed using the VEW and PCA method. The descriptive statistics are presented in Table 3.12 after which the result of the estimation based on the two methods. The forecast accuracy evaluation is presented in Table 3.15.

3.3.4.1 Descriptive Statistics

Table 3. 11: Descriptive Statistics for the Nigerian Financial Sector

Variable	Obs	Mean	Std. Dev.	Min	Max
nrvi	144	.5605088	.1483076	0	1
nils	144	.1761195	.1255663	0	1
nicb	144	.2144817	.12587	0	1
nrvb	144	.3774542	.1276868	0	1
nsbs	144	.4184637	.1638074	0	1
nrvu	144	.1298259	.0922304	0	1
nrvg	144	.2896992	.1033911	0	1
nrve	144	.2395433	.103395	0	1
ncmu	144	.6966752	.2789065	0	1
ncmg	144	.6556896	.2796055	0	1
ncme	144	.6659061	.2781275	0	1
nrva	144	.5352001	.1104132	0	1
ncma	144	.635929	.2850621	0	1
nmm	144	-9.87e-09	1.000006	-3.779383	2.963377
nbm	144	-2.31e-08	1	-2.554608	3.550122
nfm	144	1.41e-09	1.000002	-2.316786	7.354888
nem	144	-6.02e-09	1	-4.84725	4.209642
fsi_n	144	2.91e-09	1.000001	-2.316799	7.354881

Source: Estimation

In general, the variables were selected based on international literature, previous study, and systemic relevance of the variables in the Nigerian financial system and availability (Table 3.12).

3.3.4.2 Variance-Equal Weighting (VEW) Method

The result of the FSI for the Nigerian using the VEW method is presented in Figure 3.9 as noted earlier, this is the most common method used in estimating FSI in previous studies due to its simplicity when constructing and interpreting. All procedures used in 3.2.1.2 were followed. Thus, the index values can be interpreted as the number of standard deviations from the sample mean.

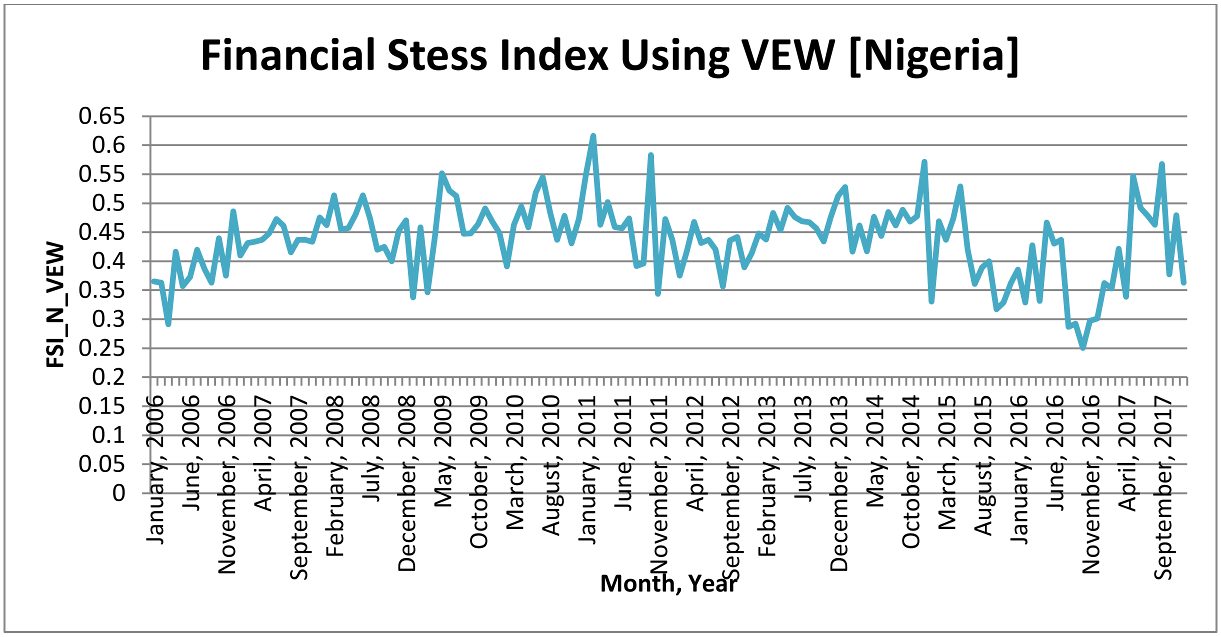


Figure 3. 9: FSI using Variance-equal weighting (VEW) Method

Source: Estimation

The result of the FSI for the Nigerian financial market using the VEW method presented in Figure 3.9 revealed some extreme cases of stress in the Nigerian financial system. However, this did not capture the entire historical extreme crisis. However, it didn't really capture properly cases of extreme events especially the more severe GFC.

3.3.4.3 Principal Component Analysis (PCA) Method

As stated in Section 3.2.1.3 that due to the limitation the VEW method noted earlier, the FSI for the Nigerian financial system was also constructed using the PCA and presented in Figure 3.10. The eigenvalues and proportion are presented in Table 3.13. The first principal component captures the larger proportion of the total variation within the stress indicators. As can be seen in Table 3.13, the first PC captures 27 percent of the total variation within the indicators. The result showed that the first two principal components, extracted from the indicators, jointly account for 50 percent of the variation within the stress indicators.

Table 3. 12: Eigenvalue and Proportion of each Component in the PCA

Components	Eigenvalue	Proportion	Cumulative

Component 1	1.2234	0.3059	0.3059
Component 2	1.0328	0.2582	0.5641
Component 3	0.9384	0.2346	0.7986
Component 4	0.8054	0.2014	1.0000

Source: Estimation

The coefficients for all the market segment indicators are positive and they represent a one standard deviation change in the respective market segments due to the fact that all the indicators are standardized. The coefficients range from a low of 0.5123 for the bond market segment to 0.64 for the foreign exchange market segment. The margin is quite large and this implies that a unit standard deviation in the foreign exchange market has an effect on the FSI (Table 3.14). In 2008, Foreign exchange earnings and revenue fell during the period due to a significant fall in oil prices to $50 per barrel from $147 per barrel earlier in the year dropped significantly after oil prices succumbed to speculative pressures during the crisis. This is quite below the $58 per barrel benchmark oil price for the 2008 budget. The government had to look to the Excess Crude Account to make up for the revenue shortfall in the 2008 and 2009 fiscal years.

Table 3. 13: Coefficient for all Market Segments

Market segment	**Composed 1**
Money market	0.2746
Bond market	-0.5123
Foreign exchange market	0.6369
Equity market	0.5064

Source: Estimation

3.3.4.4 Identification of Stress Events

One of the major criteria for evaluating FSI is its ability to identify well-known periods of financial stress (Hollo, et al. 2011). The FSI_N_PCA reflect dynamics in the surge in tension within the financial system and it's expected to rise dramatically in response to a systemic shock within the financial system. The results as presented in Figure 2 revealed previous well known financial crisis which began in 2007 and continued for the rest of 2008. The FSI_N PCA peaked at 5.05 in 2008m12, that was, shortly after the collapse of Lehman brothers in 2008m8, that is, when Lehman Brothers filed for bankruptcy protection and AIG was rescued to avoid bankruptcy. The Nigerian capital market which was performing quite well before the GFC was the first financial institution to display signs of distress in the Economy. Just as other capital markets around the globe, the Nigerian economy became an object of speculative pressures as investors disposing of their assets in reaction to the GFC.

A decade before the GFC, there was exceptional growth in the market which was mainly driven by a series of banking sector reforms. During this period, “Market Capitalization increased by over 300 per cent, from N2.90 trillion in December 2005 to N12.13 trillion in March 2008, while the All-Share Index (ASI) also rose by 161.6 per cent with the index rising from 24,085.8 in December 2005 to 63,016.56 in March 2008 ” (Sanusi, 2011). However, the emergence of the GFC eroded most of the gains of the previous years leading to it. For example, between April 2008 and March 2009, the NSE ASI and Market Capitalization fell by 67.2 percent and 61.7 percent respectively (Abimbola Hakeem Omotola, 2013). Apart from the exchange rate and reserve which were negatively affected by the GFC, inflation also rose from 6 percent in 2007 to 15.1 percent in 2008 and remained at double-digit till January 2013 when it returned to a single digit.

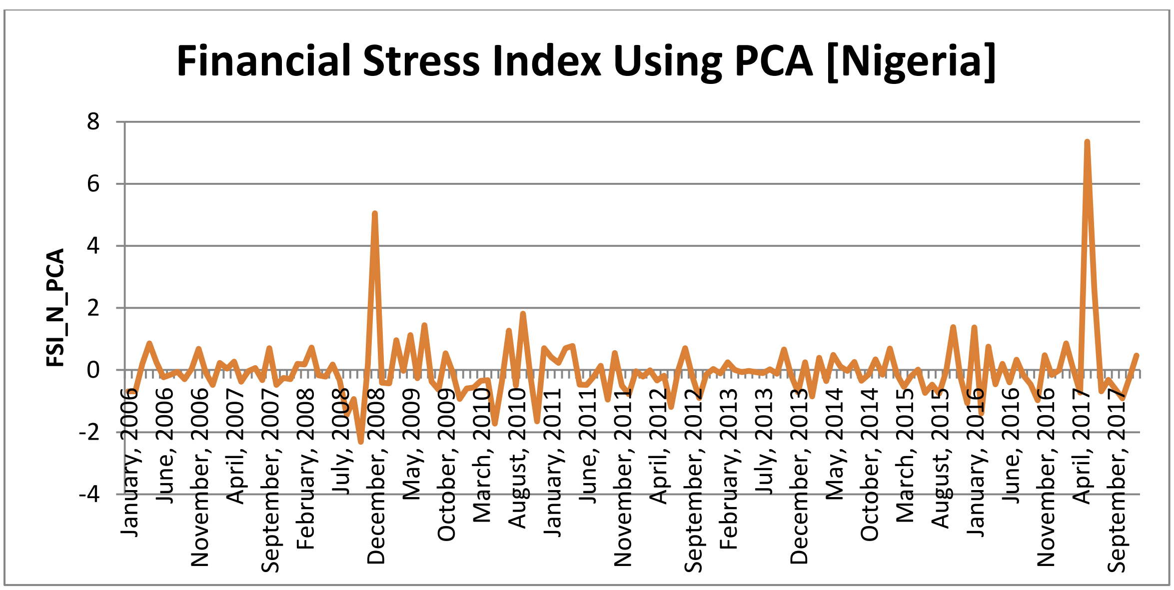


Figure 3. 10: FSI using Principal Component Analysis (PCA) Method

Source: Estimation

The GFC also threatened the stability of banks and other financial institutions in the economy. Banks' exposure to the oil and gas sector during periods of booms made them be extremely vulnerable to oil price shock as they were left to count their losses when oil prices fell (Omotola, 2013). According to Omotola (2013) during this period, huge loans had also been granted to firms and individuals who defaulted on payment together with the fact that such loans were not backed up with corresponding or suitable collateral (Omotola, 2013).

Based on the result, we also observed a mild increase in stress in late 2010 which can be linked to the sovereign debt crisis, late 2005 which coincided with the period that the country entered into recession after 25 years. The effects tend to be more severe on the economy. The FSI_N_PCA reached its maximum of 7.35 in 2017m5. This period, the country was just emerging out of recession but experienced contraction. This is due to multiple domestic challenges ranging from food crisis especially in the North Eastern part of the country due to the activities of the resilient Boko Haram Islamist group, to the long-running discontent and militancy in the Niger Delta, increasing violence between herders and farming communities spreading from the central belt southward, and separatist Biafra agitation in the Igbo south-east. Violence, particularly by the Boko Haram insurgency, has displaced more than two million people, created a massive humanitarian crisis.

3.3.4.5 Forecasting Accuracy Evaluation

For the models forecasting, the in-sample estimation was from 2006q1 to 2010q2, while the out-of-sample forecast was from 2010q3 to 2017q1. All the variables passed the necessary diagnostic test. The forecast was made using the static model (See Table 3.15).

Table 3. 14: Forecast Model Evaluation

	RMSE	MAE	MAPE	Theil	Theil U^2	Bias	Variance	Covariance	SMAPE
FSI_N_KD	0.8616	0.6967	219.8504	0.4863	0.7128	0.0679	0.0022	0.9309	133.9976

RMSE: Root Mean Square Error; MAE: Mean Absolute Error; MAPE: Mean Absolute Percentage Error; Theil: Theil inequality coefficient; Theil U^2 Coefficient; Bias, variance and covariance are the decomposed proportion of the Theil's Inequality coefficient

Source: Estimation

From the result as presented in Table 3.15, a multiple ordinary least square (OLS) analysis was conducted to evaluate the predictability and reliability of the FSI_N_KD. The result of the OLS out-of-sample (2010qq3-2017q1) forecast estimate which included real gross domestic product(rgdp) and consumer price index(CPI) as explanatory variables while the FSI_N_KD is the dependent variable is presented in Table 3.4. The result for the FSI_N_KD model affirms that the model is reliable and the FSI_N can be used for prediction of a future crisis. This is because the RMSE (0.8616), MAE (0.6967), Theil's U coefficient (0.4863), U^2 (0.7128) and SMAPE (1133.9976) are all within a reliable range. The same goes to that bias, variance and covariance decomposition of the Theil's coefficient.

3.3.5 Financial Stress Index for Emerging Africa Economies

The FSI for emerging African economies is presented here in this section. The FSI was constructed for each of the 4 emerging Africa economies using 13 stress indicators. The composite FSI for each economy covers the four major financial sectors of the economy, which include: the money market, bond market, foreign exchange market and the equity market. The summary statistic is presented in Table 3.16.

3.3.5.1 Descriptive Statistics

Table 3.16 gives a summary statistics of sub-countries that made up the FSI for the emerging African economies (FSI_EAE). FSI_K, FSI_E, FSI_N and FSI_S are the constructed FSI for Egypt, Kenya, Nigeria and South Africa respectively.

Table 3. 15: Descriptive Statistics for the Emerging African Economy

Variable	Obs	Mean	Std. Dev.	Min	Max
fsi_k	144	3.46e-09	1.000001	-3.994772	3.817068
fsi_e	144	6.93e-09	1	-1.422207	1.730913
fsi_n	144	2.91e-09	1.000001	-2.316799	7.354881
fsi_s	144	-1.95e-08	1.000003	-2.428838	1.743845
fsi_eae	144	4.25e-09	1.000002	-3.994772	3.817066

Source: Estimation

The summary statistics for the country level indicators show a mean of 0 and a standard deviation of 1. This is because the indicators were transformed using the empirical normalization. This basically, gives an indicator of zero mean and constant standard deviation.

3.3.5.3 Principal Component Analysis (PCA) Method

The financial stress index for Emerging African Economies (FSI_EAE) was constructed using the PCA method. The eigenvalues and proportion are presented in Table 3.17. The first principal component captures the larger proportion of the total variation within the stress indicators. As can be seen in Table 3.17, the first PC captures 37 percent of the total variation within the country based indicators. The result showed that the first two principal components, extracted from the indicators, jointly accounts for 64 percent of the variation within the Emerging African Economies stress indicators.

Table 3. 16: Eigenvalue and Proportion of each Component in the PCA

Components	**Eigenvalue**	**Proportion**	**Cumulative**
Component 1	1.4704	0.3676	0.3676
Component 2	1.0968	0.2742	0.6418
Component 3	0.9077	0.2269	0.8687
Component 4	0.5251	0.1313	1.0000

Source: Estimation

The coefficient for all the country-specific indicators is positive and they represent a one standard deviation change in the respective country-specific indicators due to the fact that all the indicators are standardized. The coefficients range from a low of 0.0319 for the South African financial market to 0.71 for the Kenyan financial market. The margin is quite large and this implies that a unit standard deviation in the Kenyan financial market has an effect on the FSI_EAS 23.1 times more than that of the South Africa financial market (Table 3.18).

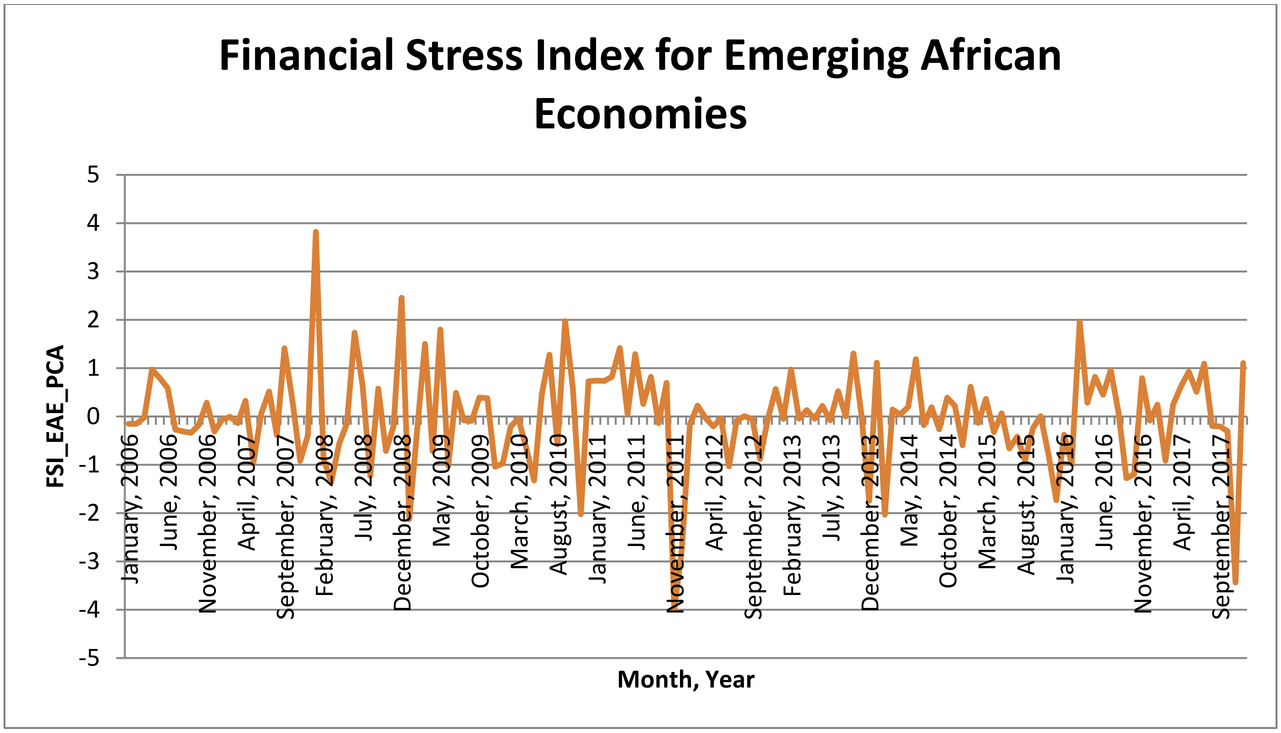
Table 3. 17: Coefficient for all Country Specific Indicators

Country	**Composed 1**
FSI_K	0.7078
FSI_E	0.0425
FSI_N	0.7044
FSI_S	0.0319

Source: Estimation

3.3.5.4 Identification of Stress Events

Major peak in the FSI is observed in the first half of 2008 (See Figure 3.11). This, therefore, implies that the FSI_EAE is a reliable coincident indicator of the global financial outbreak.



Source: Estimation

Figure 3. 11: Financial Stress Index for Emerging African Economies

The FSI_EAE also captured spike towards the end of 2010 which coincides with the European debts crisis. As noted earlier, most of the countries under consideration experienced fall in their currencies against other major currencies as well as fire sales in their stock market. For example, the shilling depreciated to the US dollar in 2008 following pressure from the global financial crisis as foreign investors “fled to safety” while consolidating their finances to meet their obligations abroad. Similar action happened in Egypt as foreign investors quickly sold off their shares in the Egyptian stock market to cover their vulnerable financial position, especially following their losses elsewhere (Ibrahim, 2012). In summary, stock markets and respective investors experienced a sharp fall in the value of their investment and general financial net worth. In South Africa, the stock market fell by 24 percent, while that (stock market) of Kenya experienced a 27 percent decline (Nyangito, 2009). Economic activities in most of these economies decreased sharply, tourism, stock exchange markets were affected negatively. For example, the JSE All Share Index lost about 31 percent in the second half of 2018, while its Nigerian counterpart (NigerianAll-Share Index) lost about 60 percent (World Bank, 2009). In Kenya and Egypt, the Nairobi Stock Exchange 20 Share Index, as well as the CASE30, fell by 48 and 56 percent respectively during the same period (Ibrahim, 2012; Were, et. al., 2012; Nyangito, 2009).

GDP growth from 7.1 percent in 2008 to around 1 percent in 2008 in Kenya, oil revenues fell in Nigeria just as global demand and oil prices dropped, while its international reserves fell by USD 19bn in 9 months (World Bank, 2009). Also in Nigeria, the Stock market lost about 46 percent of its value due to the domestic banking crisis. In the case of South Africa, growth contracted by 6.4 percent in 2009Q1 and 3 percent in 2009Q2, while about 770,000 jobs lost especially in the manufacturing (Were, et. al., 2012). The South African Rand, the Nigerian Naira and the Kenyan Shillings experienced a sharp depreciation of 23, 20 and 19 percent against major currencies (especially the US dollars) in September/October 2008 (World Bank, 2009). The increasing trend of the FSI_EAE was also detected in mid-2016; this is more of domestic crisis as most of the countries experience a number of domestic challenges ranging from political, currency crisis among others.

3.4 CHAPTER SUMMARY

This study contributes to the existing body of knowledge by constructing a financial stress index for Emerging African Economies such as Kenya, Egypt, Nigeria and South Africa. The construction of the financial stress index is important as it combines the underlying factors in the various segments of the economy at any given point in time. A Financial stress index was constructed for these economies using monthly series for 13 indicators which were grouped into four (4) market segment namely money market, bond market, foreign exchange market, and the equity market. The VEW and PCA methods were used in the aggregation of the indicators.

The result indicates that extreme values of FSIs are associated with well-known financial stress cases. It must be noted that the FSI constructed based on PCA gives importance to indicators with higher volatility. The result shows that both the domestic and international shocks created uncertainty in the economies under consideration. On the international scene, we have the financial crisis while on the domestic scene; we have slow growth, banking crisis, energy crisis, labour crisis, coupled with political uncertainty. The FSI is also useful and appropriate as the dependent variable in an early signal warning model, and as well be used to gauge the effectiveness of government measures to mitigate financial stress.

Generally, increasing trend of the FSIs was noticed for the various countries since mid-2016; this reflects more of domestic crisis as most of the countries experience a number of domestic challenges ranging from political, currency crisis among others.

The models forecasting performance was tested using the ordinary least square methods. The forecast estimate includes real gross domestic product (rgdp) and consumer price index (CPI) as explanatory variables while the FSI_N is the dependent variable and based on the model diagnostics, it was revealed that the models were well fitted and stable. For South Africa, the FSI (FSI_S_KD) developed in the study was compared with the FCI (FSI_S_KM) developed by Kabundi and Mbelu (2017). The result indicates performs better than the FCI_S_KM developed by Kabundi and Mbelu (2017). This is because the RMSE (0.8835), MAE (0.6765), Theil's U coefficient (0.5900), U^2 (3.3148) and SMAPE (114.9979) of the FSI_S_KD model were lower than that of FCI_S_KM (See Table 3.4). In the case of Nigeria (FSI_N_KD), since there was no previously known FSI constructed, the model forecasting accuracy was tested based on the result of the OLS regression. The result for the FSI_N_KD model affirms that the model is reliable and the FSI_N can be used for prediction of future crisis.

CHAPTER FOUR

EARLY WARNING SIGNAL (EWS) FOR EMERGING AFRICAN ECONOMIES

This chapter is aimed at investigating the possibility of an early warning signal model aimed at predicting the occurrence of a financial crisis in emerging African countries. The chapter is divided into 5 sections. Section 1 provides the theoretical framework and literature review. Sections 2 and 3 focus on the methodology and data respectively, while the estimation results presented in Section 4. A chapter summary is presented in Section 5.

4.1 THEORETICAL FRAMEWORK

Previous literature on the construction EWS model has majorly focused on two approaches namely the static or signal extraction approach and the dynamic or non-sample specific approach. The signal approach which was developed by Kaminsky et al. (1998) that is aimed at identifying and monitoring certain variables that tend to behave in an unusual manner in the build-up to financial or economic distress. This model is designed so as to signal an impending crisis if these indicators exceed a certain threshold value, calculated as a specific percentile of each indicator’s sample distribution. On the other hand, the dynamic choice of the threshold or non-sample-specific approach proposed by Casu et al. (2012) focuses more on the volatility of the indicators. For this, they specified the threshold as a certain number of standard deviations away from the variable’s long-run mean. Frankel and Rose (1996) alternatively proposed the utilization of logit or probit regression models to estimate the probability of an approaching currency crisis. Manasse et al. (2003) and Fuertesand Kalotychou (2006) also employed pooled logit models to examine debt crises in emerging economies.

Manasse et al. (2003)argued that logit models tend to perform better than probit ones when the dependent variable is not evenly distributed between the two outcomes, i.e. crisis and no crisis; this is usually the case as crisis events are not too common. More recently, Jedidi (2013) attempted to predict sovereign debt crises using a fixed-effects logit model while including a number of developed countries, whereas Pescatori and Sy (2007) and Lausev et al. (2011) applied a random-effects model instead. It is important to note that EWS that is based on binary dependent variable models, where the crisis variable assumes the value of one for the periods a country is hit by a crisis and zero otherwise, have an inherent endogeneity problem. This is due to the fact that the behaviour of the indicator variables is affected both by the crisis itself and the policies undertaken to mitigate it.

In addition, EWS indicators are likely to react differently during tranquil times when compared to post-crisis periods, where the economy is undergoing an adjustment process to recover from a crisis. Therefore, lumping up the observations for the tranquil periods together with that of the post-crisis period into a single zero (0) group can lead to what is known as post-crisis "bias" (Bussiere and Fratzscher, 2006). Fuertes and Kalotychou (2007) and Savona and Vezzoli (2015) tried to avoid this challenge by dropping such observation. However, this may lead to information loss. On the other hand, some authors (Peter, 2002; Manasse et al., 2003) used a dummy variable to allow for different coefficients in the post-crisis periods. However, Bussiere and Fratzscher(2006) proposed the use of a multinomial crisis variable instead that reflects all three states of the economy. Ciarlone and Trebeschi (2005), employing an earlier (2002) version of Bussiere and Fratzscher, investigated its performance in predicting debt crisis episodes in the case of emerging economies. Dawood et. al. (2017) also examined the predictive power of the econometric model in predicting the sovereign debt crisis using an Early Warning signal model for both developed and emerging economies. Their study proposed a different specification of crisis variables that allow for the prediction of new crisis onsets as well as duration, and develops a more powerful dynamic-recursive forecasting technique to generate more accurate out-of-sample warning signals of sovereign debt crises. Our results are shown to be more accurate compared to the ones found in the existing literature. The findings of the study show that in constructing an effective EWS model for the sovereign debt crisis, it is important to include variables that capture and account for the possibility of spill over from the banking sector and foreign exchange market.

The identification and prediction of the state of the financial system are very important for the design of appropriate policy such as countercyclical capital buffers which can help reduce large losses associated with the financial crisis (Drehmann and Juselius, 2014; Louzis and Vouldis, 2012). In order to predict systemic risk in the financial system an early warning signal (EWS) the multinomial logit model built by Bussiere and Fratzscher (2006) would be adopted to afford policy makers ample time to prevent or mitigate potential financial crisis (Louzis and Vouldis, 2012; Oet, Bianco, Gramlich, and Ong, 2013). Although, the EWS model was employed by Bussiere and Fratzscher (2006) with the currency crisis context, Oet et al. (2013) and Caggiano, Calice, and Leonida (2014) in the context of the banking crisis. The estimated model predicted the probability of a crisis (which takes the value of 1 for the first year, 2 for the other crisis years and 0 for non-crisis years), as a function of a vector of potential explanatory variables. While previous studies have focused on advanced economies (Barrel et al., 2010; Babecky et al., 2013) and low-income countries (Caggiano, Calice, and Leonida, 2014) there is no known study that has examined it in the context of emerging African economies.

4.2 METHODOLOGY

Pressures that lead to systemic crises are socially costly which require significant time to reverse, therefore it is important to forecast such pressure in order to prevent or in the worst case alleviate the effect of such crises Honohan and Klingebiel, 2003 (Oet et al., 2013).

Specifically, the economy is assumed to be $i = 1, \ldots . n$ which can be one of the following $j + 1 = 3$ state: tranquil period ($j = 0$), first year of crisis ($j = 1$), or crisis year other than the crisis year ($j = 2$). The probability of the economy being in a state of j is given by

$$\Pr\left(Y_t = j | X_{i,t}\right) = \frac{e^{\beta'_j X_{i,t}}}{1+\sum_{l=1}^{J} e^{\beta'_j X_{i,t}}}, \beta_0 = 0, J = 2 \qquad (1)$$

where $X_{i,t}$ is the vector of regressors of dimension K and β is the vector of the parameter to be estimated. The log-likelihood function to be maximized is

$$Ln(L) = \sum_{i=1}^{n} \sum_{j=0}^{j} d_{ij} lnPr(Y_i = j) \qquad (2)$$

where $d_{ij} = 1$ if the economy i is in state j

Setting the tranquil regime as the base outcome in order to provide identification for the multinomial logit model, which give the following $j = 2$ log-odds ratio:

$$\frac{\Pr(Y_{i,t}=1)}{\Pr(Y_{i,t}=0)} = e^{\beta'} 1^{X_{i,t}} \qquad (3)$$

and

$$\frac{\Pr(Y_{i,t}=2)}{\Pr(Y_{i,t}=0)} = e^{\beta'} 2^{X_{i,t}} \qquad (4)$$

In Equation (3), the vector of the parameter β_1 measures the effect of a change in the independent variables $X_{i,t}$ on the probability of entering a systemic financial crisis relative to the probability of being in tranquil times. On the other hand Equation (4),β_2 measures the effect of a change in the independent variable $X_{i,t}$ on the probability of remaining in a state of crisis relative to the probability of being in tranquil times.

4.3 DATA

The study will use stock returns of major bank holding companies (publicly traded firms) from 1980 to 2017. The choice of the explanatory variables is based on both the relevant literature (Demirgüç-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999) and on the structural features of the banking system of the sample of economies at hand. Data used in this study include the real gross domestic growth rate (rdgp), inflation and exchange rate depreciation to measure economic activities, macroeconomic stability and foreign exchange risk respectively. Others are domestic credit to the private sector, FX net open position, ratio of broad money to reserve ratio (bmm2), ratio of credit as a percentage of GDP (cgdp), and liquidity is the ratio of loans to deposit, net open position is the ratio of net foreign asset to GDP while leverage is the ratio of capital to asset. The ratio of M2 to official reserves captures the ability of the economy to withstand a reversal in capital flows, especially in the presence of a currency peg. Therefore, the higher the value for this variable, the higher the vulnerability to capital outflows, and hence the probability of incurring a banking crisis. Similarly, excessive credit growth can trigger bank problems through a generalized deterioration in asset quality and/or a reduction in liquidity, especially in the context of volatile funding sources (See Table 4.2.1 for a summary). All the data apart from FSI and exchange rate were sourced from the world bank online database. Data on FSI was constructed by the researcher (See Chapter 3 for details). Data on exchange rate was sourced from country-specific central banks and the World Bank (World development indicators).

Table 4.1: Summary of Data

Variable name	Description	Measure
Dcrp	Domestic credit to the private sector (% of GDP)	Monetary condition
Infr	Inflation	Macroeconomic stability
Rgdpg	the real gross domestic product growth rate	Macroeconomic stability
bmm2	The ratio of M2 to foreign exchange reserves of the Central Bank	Monetary condition
exhr	Rate of change of the nominal exchange rate vs. the US dollar. An increase indicates a depreciation of the domestic currency	Foreign exchange risk
Fxop	The ratio of net foreign assets to GDP	Liquidity
Dgdp	Debt to GDP ratio	Leverage
Sdtd	short term debt to total debt	leverage
FSI	Financial stress index	Financial risk
top	Trade openness	International trade
FDI	Foreign direct investment, net inflows (% of GDP)	Capital flow

4.4 ESTIMATION RESULT

The estimated result of the EWS model using the multinomial logit regression is presented in this section. The summary statistics are presented in Table 4.2 while the multinomial logit regression result is presented in Table 4.3. As a way of robustness check, the multinomial logit model was again estimated using the robust standard error and the result was similar to the previous one.

4.4.1 Summary Statistics

The summary statistics are presented in Table 4.2.

Table 4. 1: Summary Statistics

	BMM2	DCRP	DGDP	EXHR	FDI	FXOP	INFR	RGDPG	SDTD	TOP

Mean	51.20674	46.60852	50.01394	12.26244	1.707631	138.3157	13.10693	2.381334	12.79045	52.03029
Median	44.38308	26.96424	35.14038	4.348408	1.069333	27.50078	10.31503	3.191601	10.75335	53.08161
Maximum	98.13613	160.1248	228.3718	347.5464	10.83256	1213.921	72.8355	94.79607	46.1849	82.17668
Minimum	13.23075	8.70966	4.130462	-99.7564	-1.15086	-20.674	-0.69203	-94.5872	0	20.72252
Std. Dev.	24.64209	42.69319	40.83722	41.62144	1.939553	256.3356	11.01774	13.16585	10.74823	12.25602
Skewness	0.369374	1.421256	1.487491	4.468285	2.107457	2.52955	2.816907	-1.26827	1.036848	-0.31546
Kurtosis	1.801495	3.64594	5.574482	34.79195	8.600391	8.958168	12.59933	40.71276	3.743178	3.188954
Jarque-Bera	12.5537	53.81506	98.03034	6907.073	311.1559	386.9302	784.6174	9048.345	30.73268	2.74712
Probability	0.001879	0	0	0	0	0	0	0	0	0.253204
Sum	7783.425	7084.495	7602.119	1863.891	259.5599	21023.98	1992.254	361.9627	1944.149	7908.604
Sum Sq. Dev.	91692.14	275229	251819.4	261584	568.0415	9921898	18329.98	26174.28	17444.21	22681.7
Observations	152	152	152	152	152	152	152	152	152	152

Source: Estimation

4.4.2 Estimated result of the EWS model for Emerging African Economies

The result for the EWS model estimated for emerging African countries is presented in Tables 4.3 and 4.4 respectively. The result based on the Observed information matrix (OIM) optimization technique for the standard error is presented in Table 4.3, while that of the robust standard error is presented in Table 4.4. The OIM is the matrix of second derivatives, usually of the log-likelihood function and is based on asymptotic maximum-likelihood theory. It is usually preferred when estimating small or medium dataset. The OIM estimator of the VCE is based on asymptotic maximum-likelihood theory (Hardin, et al. 2007).

Table 4. 3: EWS model for Emerging African Economies

	Explanatory variables	Coef.	Std. Err.	Z	P>z	[95% Conf. Interval]	
Crisis							
	rgdpg	-0.0289	0.0506	-0.5700	0.5670	-0.1280	0.0702
	dcrp	-0.0417	0.0391	-1.0700	0.2860	-0.1184	0.0349
	infr	0.2540	0.1507	1.6900	0.0920**	-0.0413	0.5492
	bmm2	0.1784	0.0647	2.7600	0.0060*	0.0515	0.3052

	exhr	-0.0119	0.0356	-0.3300	0.7380	-0.0816	0.0578
	fxop	0.0188	0.0055	3.4000	0.0010*	0.0079	0.0296
	dgdp	-0.1863	0.0936	-1.9900	0.0470*	-0.3697	-0.0028
	sdtd	0.3078	0.1589	1.9400	0.0530*	-0.0035	0.6192
	top	0.3666	0.1878	1.9500	0.0510**	-0.0014	0.7347
	fdi	-0.1807	0.4588	-0.3900	0.6940	-1.0799	0.7185
	_cons	-36.3146	13.1983	-2.7500	0.0060	-62.1827	-10.4465
Post Crisis							
	rgdpg	-0.0046	0.0366	-0.1300	0.8990	-0.0763	0.0670
	dcrp	0.0092	0.0099	0.9300	0.3510	-0.0102	0.0286
	infr	0.0614	0.0703	0.8700	0.3830	-0.0764	0.1992
	bmm2	0.1046	0.0279	3.7500	0.0000*	0.0499	0.1594
	exhr	-0.0010	0.0138	-0.0700	0.9430	-0.0281	0.0261
	fxop	0.0154	0.0038	4.0400	0.0000*	0.0079	0.0229
	dgdp	-0.0602	0.0224	-2.6800	0.0070*	-0.1042	-0.0162
	sdtd	0.0246	0.0361	0.6800	0.4960	-0.0462	0.0954
	top	-0.0296	0.0432	-0.6900	0.4930	-0.1142	0.0550
	fdi	-0.2848	0.2283	-1.2500	0.2120	-0.7323	0.1627
	_cons	-6.5254	2.6867	-2.4300	0.0150	-11.7913	-1.2595
	Number of obs		152				
	LR chi2(18)		124.12				
	Prob > chi2		0.0000				
	Pseudo R2		0.5525				
	Log-likelihood		-50.2572				

Source: Estimation

The estimation results of the EWS model is presented in Table 4.3. The result of the first panel of Table 4.3 is based on the probability of entering a crisis compared to being in a tranquil time. This result shows that the debt exposure variables (dgdp and sdtd which are the ratio of external debt to GDP and ratio short term debts to total debts respectively) are significant indicators in the model. This is in line with the study of Lausev et al. (2011), Jedidi (2013) and Dawood et al (2017). Also, the result shows that bmm2 which measure the ability of the economy to withstand reversal in capital flows was also significant in determining the probability of entering into crisis. Furthermore, the result shows that inflation rate, FX net open position and trade openness are all significant in determining the probability of experiencing financial crisis. For example, rising inflation make external debts servicing more expensive while trade openness makes the African economies susceptible to foreign shock Caggiano et al. (2014). The result also found a negative credit growth and capital inflows before the crisis although not significant. This result confirms the significance of financial stability framework that fits Africa's emerging economies characteristics such as rising debt profile liquidity and currency risk exposure. According to Caggiano et al. (2014), exposure to currency risk is a source of threat to the soundness of the financial system.

This result suggests that emerging African economies are more likely to collapse when debt rises and there is no capacity to withstand capital flow reversal as well as excessive FX risk due to financial dollarization. The second panel of Table 4.3 focuses on the probability of remaining in a crisis state as against being in a tranquil time. The results are in line with expectations: on the one hand, a negative and significant coefficient for bmm2 indicates that a rise in the ratio of the money supply to international reserve increases the likelihood of remaining in a state of crisis. Similarly, a positive and significant coefficient for sdtd suggests that rising debt exposure increases the probability or likelihood of the economies remaining in a state of crisis.

4.4.3 Robustness Standard Error Test of the EWS model for Emerging African Economies

A robust standard error of the model was estimated and the result is presented in Table 4.4.

Table 4. 4: Robust Standard Error Test of the EWS model for Emerging African Economies

	Explanatory variable	Robust Coef.	Std. Err.	Z	P>z	[95% Conf. Interval]

Crisis							
	rgdpg	-0.0289	0.0183	-1.5800	0.1130	-0.0647	0.006854
	dcrp	-0.0417	0.0246	-1.7000	0.0900**	-0.0899	0.006463
	infr	0.2540	0.1821	1.3900	0.1630	-0.1029	0.610856
	bmm2	0.1784	0.0754	2.3600	0.0180*	0.0305	0.326233
	exhr	-0.0119	0.0170	-0.7000	0.4820	-0.0451	0.021314
	fxop	0.0188	0.0103	1.8300	0.0670**	-0.0013	0.038856
	dgdp	-0.1863	0.0892	-2.0900	0.0370*	-0.3610	-0.0115
	sdtd	0.3078	0.1410	2.1800	0.0290*	0.0314	0.584243
	top	0.3666	0.2278	1.6100	0.1080	-0.0798	0.813085
	fdi	-0.1807	0.2961	-0.6100	0.5420	-0.7610	0.399634
	_cons	-36.3146	19.0282	-1.9100	0.0560	-73.6092	0.980093
Post Crisis							
	rgdpg	-0.0046	0.0199	-0.2300	0.8160	-0.0437	0.034429
	dcrp	0.0092	0.0090	1.0300	0.3030	-0.0083	0.026812
	infr	0.0614	0.0643	0.9500	0.3400	-0.0646	0.187383
	bmm2	0.1046	0.0410	2.5500	0.0110*	0.0243	0.18498
	exhr	-0.0010	0.0082	-0.1200	0.9030	-0.0170	0.015
	fxop	0.0154	0.0089	1.7300	0.0830**	-0.0020	0.032822
	dgdp	-0.0602	0.0283	-2.1300	0.0330*	-0.1157	-0.00472
	sdtd	0.0246	0.0225	1.0900	0.2750	-0.0196	0.068791
	top	-0.0296	0.0324	-0.9100	0.3610	-0.0931	0.03393
	fdi	-0.2848	0.2039	-1.4000	0.1630	-0.6844	0.114859
	_cons	-6.5254	3.4209	-1.9100	0.0560	-13.2302	0.179473
	Number of obs		152				
	LR chi2(18)		124.12				
	Prob > chi2		0.0000				
	Pseudo R2		0.5525				
	Log-likelihood		-50.2572				

Source: Estimation

The estimated result of the EWS model using the robust standard error is similar to the previous one in Table 4.3. The result as presented in Table 4.4 confirms dcrp, bmm2, fxop, dgdp, and sdtd are all significant indicator of financial crisis for the pre-crisis period with respect to the tranquil period. However, after the crisis, bmm2, fxop and dgdp are significant indicators of the financial crisis with respect to tranquil periods. As noted above, a positive and significant coefficient for sdtd suggests that rising debt exposure increases the probability or likelihood of the economies remaining in a state of crisis. This may suggest that African countries are at a risk in the light of the rising debt profile, especially debts from China. This raises concerns about African countries defaulting on their debts. According to an IMF report in April 2018, at least 40 percent of low-income countries in the region are either in debt distress or at high risk (Madowo, 2018). Similarly, in 2015, the China Africa Research Initiative at the Johns Hopkins School of Advanced International Studies raised an alarm that African countries might be unable to repay Chinese loans "due to fluctuating commodity prices and decreasing absorptive capacity" (Madowo, 2018).

4.4.4 Diagnostic Tests

The lower panel of Tables 4.3 and 4.4 provides information about the performance of the multinomial logit model in terms of the predictive power of the EWS model estimated. It is important to assess the good-of-fit of the EWS model by looking at the Pseudo McFadden R^2, log-likelihood ratio and chi^2 wald test. The number of observations used in each regression (N) over the period 1980–2017, the Pseudo McFadden's R^2, the log-likelihood ratio, and the chi^2 wald test are shown on the lower panel of Tables 4.2 and 4.3. The pseudo-R^2 statistics is useful in assessing the predictive strength of the logistic regression model. That is the proportion of variance in the dependent variable associated with the predictor (independent) variables. The pseudo-R^2 is 0.55; this means that the independent variables can well predict the dependent variable. This is also confirmed by the Wald test statistic which is significant at 5 percent and therefore suggests that the parameters associated with the logistic regression model are simultaneously not zero. This result suggests that the model has good predictive power.

4.5 CHAPTER SUMMARY

This chapter investigated the possibility of an early warning signal model aimed at predicting the occurrence of the financial crisis in emerging African countries. The multinomial logistic regression that assumes 0 for the tranquil period, 1 for crisis period and 2 for a period after the crisis was employed in order to avoid what is known as post-crisis bias and information loss. The multinomial logit model reduces the likelihood of false alarm and missed crisis when compared to the binomial logit model. Four emerging African economies such as Egypt, Kenya, Nigeria and South Africa were considered in the study.

This result shows that the debt exposure variables are significant indicators that predict a crisis in emerging African countries. This is in line with the study of Lausev et al. (2011), Jedidi (2013) and Dawood et al (2017). African countries are prone to bad debts due to the high cost of repayment of loans from advanced countries and also due majorly to the level of corruption within the system. It was also noted that money supply which measures the ability of the economy to withstand reversal in capital flows was also significant in determining the probability of entering into crisis. Furthermore, the result shows that inflation rate, FX net open position and trade openness are all significant in determining the probability of experiencing financial crisis. For example, rising inflation make external debts servicing more expensive while according to Caggiano et al. (2014) trade openness makes the African economies susceptible to foreign shock. The result also found a negative credit growth and capital inflows before the crisis although not significant.

In summary, the result suggests that emerging African economies are more likely to face financial crisis as debts continue to rise without a corresponding capacity to withstand capital flow reversal as well as excessive FX risk due to currency exposure. The result further indicates that rising debt exposure increases the probability or likelihood of the economies remaining in a state of crisis. This result confirms the significance of financial stability framework that fits Africa's emerging economies characteristics such as rising debt profile liquidity and currency risk exposure. According to Caggiano et al. (2014), exposure to currency risk is a source of threat to the soundness of the financial system. The model goodness-of-fit and predictive power which was tested based on the value of the pseudo-R^2 statistics is 0.55; this means that the independent variables can well predict the dependent variable.

CHAPTER FIVE

STRESS TESTING THE RESILIENCE OF THE FINANCIAL SYSTEM TO ADVERSE MACROECONOMIC SHOCKS IN EMERGING AFRICAN ECONOMIES

This chapter focuses on the econometric assessment and analysis of the vulnerabilities of financial systems to credit risk through stress testing. Macro stress testing is aimed at estimating the impact of credit risk shock on macroeconomic as well as financial sectors. A two-step approach was employed in this chapter. The first step involves analyzing the determinants of credit risk in 4 Emerging African economies during the period 2006m1 to 2012m12 using the panel Auto Regressive Distribution Lag (ARDL) model. Second, the vector autoregressive (VAR) models were employed to assess the resilience of the financial system as well as the economy to adverse credit risk shocks. The chapter is divided into four broad sections. The theoretical framework and empirical review are presented in Section 1, while data and methodology are presented in Section 2. Section 3 focuses on estimated results and discussion, while the summary of the chapter is presented in Section 4.

5.1 THEORETICAL FRAMEWORK AND EMPIRICAL REVIEW

Stress testing is a multi-step simulation process for examining the vulnerability and exposure in the financial system (Bhattacharyay, 2009). It is a popular risk management tool to evaluate the potential impact of an extreme event on a financial firm or a financial sector (Huang et al., 2009). The stress test provides information on the nature of the system under exceptional but plausible shocks or the impact of a range of future shocks to certain macroeconomic variables of the system (Bhattacharya, 2009). A stress test is useful for quantifying losses that may be incurred during crisis situations where normal market relationships break down (Dowd, 2011). It is in some way a compliment to probability-based risk measures such as VaR and expected shortfall (ES). For example, the VaR gives us the maximum likely loss at a certain probability, but gives no idea of the loss we might suffer if we experience a loss in excess of VaR, while ES provides the expected value of a loss in excess of VaR, but silent on the distribution of “tail losses” other than its expected value (Dowd, 2011). By contrast, the stress testing technique is designed to give more information about losses in the bad state although it does not tell us the likelihood of such bad state or shocks occurring as the VaR and ES technique do (Bhattacharya, 2009a; Dowd, 2011).

The focus is on the macroeconomic drivers of credit risk. Credit risk is measured by the ratio of non-performing loans to total loans. As noted earlier, stress tests in the financial sector provide information on a system's potential losses under exceptional but plausible shocks; thereby assisting policymakers assess the significance of the system's vulnerabilities. The value added by system stress tests derives from a consultative process that combines a forward-looking macroeconomic perspective, a focus on the financial system as a whole, and a uniform approach to the assessment of risk exposures across institutions. System stress tests can complement those of individual institutions and provide a cross-check for other types of analysis. As noted earlier in chapter 2, the FSAP stress tests stimulated widespread research interest in developing new techniques.

Also, due to their financial stability mandate, central banks, supervisors and policymakers are mostly concerned about quantifying the macro-to-micro linkages as well as developing models for assessing it. Macro-scenario stress testing is aimed at estimating the financial sector effects of multiple shocks to macroeconomic and financial variables are estimated using different models (Foglia, 2009). The stress scenario's effects on macroeconomic conditions are typically measured using (i) a structural econometric model, (ii) vector autoregressive methods, and (iii) pure statistical approaches. A number (Jones, Hilbers, and Slack, 2004;) of stress-testing methodologies employ an existing structural macroeconomic model (for example, one used by the central bank for forecasts and policy analysis) to forecast the levels of key macroeconomic indicators under some hypothetical stress scenarios. Under this approach, a set of initial shocks are taken as exogenous inputs, and their interactions with the other macroeconomic variables are projected over the scenario horizon (Foglia, 2009). This type of model imposes consistency across predicted values in the stress scenario and may also allow for endogenous policy reactions to the initial shock (Foglia, 2009). However, this method of stress testing scenarios requires a great deal of expertise. Alternatively, the vector autoregression (VAR) or vector error-correction models (VECMs) can be used to estimate the joint impact of the initial shock on macroeconomic variables, and the vector process is used to project the stress scenario's combined impact on this set of variables. VAR models have appeal because they are a flexible and relatively simple way of producing a set of mutually consistent shocks, although they do not include the economic structure that is incorporated in the macro modelling approach. A number of central banks such as the Bank of Japan (BoJ), Bank of Spain (BoS), European Central Bank (ECB) and Bank of England (BoE). For example, the BoJ (2007) estimated a VAR model comprising five macroeconomic variables such as gross domestic product (GDP), inflation rate, bank loans outstanding, effective exchange rate, and the overnight call rate. Also, Van den End, Hoeberichts, and Tabbae (2006) and Jim´enez and Mencıa (2007) use a VAR structure to model the response of macroeconomic factors to a shock in a credit-risk model. Castren, Dees, and Zaher (2008) employed a global vector autoregressive (GVAR) model based on country- or region-specific VECMs, where domestic and foreign variables interact simultaneously; the endogenous variables included in the country-specific models are real output, the rate of inflation, real equity prices, and short- and long-term interest rates. In a similar manner, the BoE employed a two-country version of the GVAR approach, modeling the UK and U.S. economies only, with macroeconomic variables.

The last approach is the pure statistical scenario design which was employed by the Oesterreichische Nationalbank (OeNB), in its Systemic Risk Monitor (SRM). In this approach, macroeconomic and financial variables are modelled through a multivariate t-copula. The copula approach has two important advantages. First, the marginal distributions can be different from the multivariate distribution that characterizes the joint behaviour of the variables. Second, the co-dependence between the macro-financial variables displays tail dependence (that is., "correlation" increases under stress scenarios). However, as a "purely" statistical approach, it is not as well suited for policy analysis. Drehmann (2008) underlies how important is the suitability for storytelling for proper communication of policy evaluations and how using general equilibrium structural macroeconomic models may be appropriate in highlighting the key macroeconomic transmission channels from shocks to impact on credit risk. By contrast, risk managers at financial institutions are less interested in the unwinding of the transmission mechanism and are more focused on the model forecast performance, which can guide their day-to-day decision-making process. As noted in section 2.8 (Figure 2.5), stress testing first involves describing the scope of the analysis after which a macroeconomic stress scenario will be designed and calibrated. The next step will be to quantify the impact of the simulated scenario on the solvency of the financial sector, either through assessing the balance sheet vulnerabilities during economic downturns or integrating the analysis of multiple risk factors into a probability distribution of aggregate losses. The interpretation of the results and feedback effect are accounted for lastly (Sorge and Virolainen, 2006; Berner, 2016). The methodology and data issue are discussed in the next section.

5.2 METHODOLOGY AND DATA

The major aim of this study is to see how resilient the financial system in emerging African economies such as Egypt, Kenya, Nigeria and South Africa. The stress testing involves the following steps: (1) Identifying major vulnerabilities, risks, and exposure or potential sources of shocks, such as interest rates, exchange rates, credits, equity prices, liquidity, interbank contagion and volatility; (2) Defining coverage and identifying data: all systemically relevant institutions and exposures; (3) establishing key linkages between the financial system and the real economy- a formal macroeconomic model or macro-simulation models; (4) Selecting and implementing methodology-crunching numbers: translating the various output of the macroeconomic model into financial institutions' balance sheet and income statements, and (5) Interpreting and using the results: policymakers compare the impact of a common set of shocks on different institutions. For interpreting stress tests, one should consider the limits and assumptions on which they are built (Jones et. al., 2004 and Cihak, 2003).

For this study, macroeconomic variables such as output gap, interbank rate, policy rate, stock market index, unemployment rate, exchange rate, inflation rate and nonperforming loan ratio were used (See Summary in Table 5.1).

Monthly data from 2006m1 to 2017m12 was used. Based on the literature (Love and Ariss, 2013; Espinoza and Prasad, 2010; Nkusu, 2011) two methods were employed in this section. First, the determinants of credit risk were estimated using a panel Autoregressive Distributed Lag (ARDL) method using both the Mean Group (MG) and Pooled Mean Group (PMG) models. The Hausman test was conducted to choose the most efficient of the MG and PMG model. The result of the Hausman test indicated that the PMG model should be used. After which a vector autoregression (VAR) approach was implemented to assess the extent to which adverse macroeconomic shocks affect the financial system. This approach is used to estimate the impact of changes in macroeconomic variables on credit risk which is proxied by nonperforming loan ratio.

Table 5. 1: List of risk factor and their expected relation to the quality of loan portfolio

Group	Variable	Expected relationship to the growth of NPLs	Data source
NPLs	NPLs		Federal reserve bank website (FRED)
Cyclical indicators	Output gap (GSP)	negative / -	World Bank
Price stability indicators	Inflation (INF)	ambiguous +/-	World Bank
Household indicators	Unemployment rate (UMP)	positive / +	World Bank
Financial market indicators	3M interbank rate (IBR)	positive / +	IMF~ International financial statistics
Financial market indicators	Stock market index (SID)	negative / -	Bloomberg/investing.com
External indicators	Real Exchange rate depreciation against the dollar (EXR)	ambiguous +/-	World Bank

5.2.1 Mean group

Pesaran, Shin and Smith (1995) suggest Mean Group (MG) model in order to resolve the bias due to heterogeneous slopes in dynamic panels, the MG estimator, on the other hand, provides the long-run parameters for the panel through making an average of the long-run parameters from ARDL models for individual countries. For instance, if the ARDL model follows:

$$Y_t = \alpha_i + \emptyset_i Y_{i,t-1} + \beta_i X_{it} + \varepsilon_{it}$$

where, i represent for individual country $i = 1, 2, 3, \ldots . N$ and the long run parameter is θ_i

$$\theta_i = {}^{\beta_i}/_{1 - \emptyset_i}$$

while the MG estimator for the whole panel is given by

$$\hat{\theta} = {}^{1}/_{N} \sum_{t=1}^{N} \theta_i$$

$$\hat{\alpha} = {}^{1}/_{N} \sum_{t=1}^{N} \alpha_i$$

The Above equations reveal how the model estimates separate regressions for each country and calculate the coefficients as an unweighted mean of the estimated coefficients for the individual countries. This does not impose any restriction. It allows for all coefficients to vary and be heterogeneous in the long-run and short-run. However, the necessary condition for the consistency and validity of this approach is to have a sufficiently large time-series dimension of the data. The Pool Mean Group, on the other hand, was applied in order to detect the long and short run association between credit risk proxied by nonperforming loan ratio and macroeconomic variables, and also investigate the possibly heterogeneous dynamic issue across countries. For the dynamic panels analysis, this study applied the panel Autoregressive distributed lag ARDL (p,q) estimation technique model in the error correction form and then estimate the model based on the mean group (MG) presented by Pesaran and Smith (1995) and Pooled mean group (PMG) estimators developed by Pesaran et al. (1999). The ARDL specification is formulated as follows (Loayza and Ranciere, 2006):

$$Y_{it} = \sum_{j=1}^{p-1} \emptyset_y^i (Y_i)_{t-j} \sum_{j=0}^{q-1} \vartheta_y^i (X_i)_{t-j} + \delta^i (Y_i)_{t-1} + \varphi_i + \varepsilon_{it}$$

where $X_{i,t-j}$ is the vector of $kx1$ explanatory variables for group i and φ_i is the fixed effect. In some cases, the panel can be unbalanced, that it, $p \ and \ q$ may vary across countries. This model can be reparametrised as a panel vector error correction model (VECM) system as follows:

$$\Delta Y_{it} = \theta_i \left(Y_{i,t-1} - \beta_i X_{t-1} \right) + \sum_{j=1}^{p-1} \emptyset_y^i \Delta Y_{i,t-j} \sum_{j=0}^{q-1} \vartheta_y^i \Delta X_{i,t-j} + \varphi_i + \varepsilon_{it}$$

where β_i represent the long-run parameters and θ_i represent equilibrium or error correction parameters. The pooled mean group (PMG) restriction is that the elements of β are common across countries:

$$\Delta Y_{it} = \theta_i[Y_{i,t-1} - \beta_i X_{t-1}] + \sum_{j=1}^{p-1} \emptyset_y^i \Delta Y_{i,t-j} \sum_{j=0}^{q-1} \vartheta_y^i \Delta X_{i,t-j} + \varphi_i + \varepsilon_{it}$$

where Y is the non-performing loans (npls) and X is the set of explanatory variables including interest rate, inflation, GDP output gap, unemployment rate and equity market index. $\emptyset \; and \; \vartheta$ are short-run dynamic coefficients of dependent and independent variables respectively. β represent long-run coefficients, θ_i is the speed of adjustment to long-run equilibrium, while the subscripts $i \; and \; t$ represent the countries and time respectively. If $\theta_i = 0$, then there is no evidence that variables have long run association. It is expected that θ_i is negative and statistically significant under the prior supposition that variables indicate a convergence to long run equilibrium in case of any disturbance.

5.2.2 Macro Testing Framework

To test the system's ability to withstand adverse macroeconomic shocks, the NPLs is subjected to shocks in a vector autoregressive (VAR) framework from interest rate, inflation, GDP output gap, unemployment rate and equity market index. The VAR model is believed to be a superior technique for modelling stress test (Foglia, 2009; Banerjee and Murali, 2015). The VAR model is flexible, dynamic and robust as it captures the linear interdependences among a set of selected k endogenous variables (Banerjee and Murali, 2015). Within the VAR framework, k endogenous variables are specified as linear functions of each other over a specific time t. In addition, exogenous variables can as well be included in the model to account for exogenous shocks.

The p order VAR or $VAR(p)$ is thus given as

$$Y_t = L + B_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \varepsilon_t$$

where, Y_t is the vector of endogenous K variables, p is the VAR order indicating the lag length, t is the time period, L is the vector of $K \; x \; 1$ constants, B is the coefficient $K \; x \; K$ matrix and ε_t is the error terms.

Based on the dynamic interactions among the K endogenous variables, interpreting the VAR results is aided by a set of post-VAR estimations such as Impulse Response Function (IRF), Variance Decomposition (VDC) as well as Granger Causality test. These post-VAR estimations are very important as they help in breaking down and interpreting the dynamic interrelationships of the K variables that the VAR captures.

5.3 ESTIMATION RESULTS

The objective here is to analyze the vulnerability of financial systems to credit risk through macro stress testing in emerging African economies. Empirical results are presented here. The section is divided into four subsections. Summary statistics are presented in the first sub-section while the panel unit root test is presented in the second subsection. The PMG estimations are reported in the third sub-section, the macro testing result is presented in the fourth sub-section. It must be noted that the PMG estimation technique was employed based on the Hausman test. The test indicated that the PMG is more efficient.

5.3.1 Summary Statistics

The summary statistics are presented in Table 5.2.

Table 5. 2: Summary Statistics

	Obs	Mean	Std.Dev	Min	Max
npls	576	8.325958	6.198975	0.967795	37.97912
gap	576	0.49996	1.942273	-4.89398	4.374986
inf	576	0.003197	0.043958	-0.16734	0.175574
ump	576	13.08295	7.354443	3.595753	27.33
lex	576	3.451389	1.390494	1.692223	5.722899
lnalsi	576	8.106245	2.445886	3.96689	11.09213
ibr	576	9.214312	5.31408	0.77	64.58

Source: Estimation

Table 5.2 shows the summary statistics of the variables used in the study. There is a significant variation in minimum and maximum values of different measures of macroeconomic variables. For example, for the case of the output gap, there is significant variation as it ranges from –4.8939 to 4.37498. Same for inflation which ranges from -0.1673 to 0.175574, ditto other variables.

5.3.2 Results of Panel Unit Root Tests

With the increase in the time period of analysis, dynamic panels; nonstationarity is a very important issue and in the present study, this issue has been taken into consideration by applying Levin, Lin and Chu (LLC) and Im, Pesaran and Shin (IPS) unit root tests. The results of the panel unit root tests for output gap, inflation rate, unemployment rate, stock market index, exchange rate, interbank rate and nonperforming loans (See Appendix 2). The estimated *t-star* statistics of the Levin-Lin-Chu (LLC) test, $t-$bar statistics for the Im-Pesaran-Shin (IPS) test and λ-values for the Fisher $P(\lambda)$ test with their accompanying *p*-values were reported. Despite the study by Im et al. (1997) that have demonstrated by Monte Carlo simulations that their panel test suggest better finite sample performance of the $\psi_{\bar{t}}$ over Levin-Lin-Chu's t^*, and a study by Breitung (1999) that showed the Maddala and Wu (1999) panel unit root tests have considerable more power relative to the IPS test, in all cases the three panel unit root test results are consistently indicating that all the areas a group. The null hypothesis of a unit root in level cannot be rejected at the 5 percent level of significance, while the null hypothesis of a unit root in first difference can be rejected at the 5 percent level of significance (See Appendix B-1). When the test was conducted on an individual and country-specific basis, the Augmented Dickey-Fuller (ADF) unit root test also show that all the variables are integrated of order one. In order words, they are *I(1)* (See Appendix B-2).

5.3.3 Panel Data Result

The variables used in this study were divided into two groups (macroeconomic and financial) and the results are presented in Tables 5.3 and 5.4 respectively. This reason is that panel ARDL usually breaks down when more variables are estimated together. The results of these models provide the short-run and long-run impacts of macroeconomic and financial variables on credit risk measured by nonperforming loans. The Hausman test results which indicated that the PMG estimation technique is used are presented in Appendix D-5 and D-6. However, the mean group (MG) technique was still used and the results presented in Appendix D-1 and D-3. The results indicated not a significant relationship among the variables except IBR which manifested a significant relationship with NPL.

5.3.3.1 PMG Estimate for Model One

The PMG (Panel ARDL 2 1 0 2 0 2 0 2) estimation result for the impact of macroeconomic variables on credit risk is presented in Table 5.3. The macroeconomic variables include output gap, inflation rate and unemployment rate.

Table 5. 3: Panel ARDl Result Model one (dependent variable NPLs)

	Model one Pooled mean group estimation						
	Long Run Coefficients						
	NPL	Coef.	Std.	Err.	z P>z	[95%	Conf.Interval]
ECT							
	GAP	0.363747	0.230263	1.58	0.114	-0.08756	0.815054
	INF	-16.3937*	4.95374	-3.31	0.001	-26.1029	-6.68457
	UMP	-0.67785*	0.190384	-3.56	0.000	-1.051	-0.30471
SR	**Short Run**						
	ECT	-0.03375***	0.017814	-1.89	0.058	-0.06867	0.001164
	GAP						
	D1.	-0.14342	0.13606	-1.05	0.292	-0.41009	0.123257
	INF						
	D1.	1.370927	3.314604	0.41	0.679	-5.12558	7.867432
	UMP						
	D1.	0.601306	0.594631	1.01	0.312	-0.56415	1.766761
	_cons	0.502062	0.263814	1.9	0.057	-0.015	1.019128
Hausman	chi2(3)=	(b-B)'[(V_b-V_B)^(-1)](b-B)					
	chi2(3)=		4.19				
	Prob>chi2 =	0.2412					

Source: Estimation.

*, **, *** means significance at the 1 percent, 5 percent and 10 percent level of significance respectively

a) Long-Run Results Model One

The PMG estimation result for the impact of macro variables on credit risk is presented in Table 5.3. The long run estimates are presented in the upper panel while that of the short run are presented in the lower panel. The result shows that inflation and unemployment has a negative and significant impact on NPL at the 1 percent level of significance. Essentially, a 1 percent increase in inflation and will result in a 16.39 percent decline in NPL. This can be explained in the sense that as inflation increases, property prices are appreciated, this will ultimately reduce the value of loans, therefore it is expected that inflation may reduce NPL (Climent-Serrano, 2017). However, the coefficient of unemployment did not follow theoretical expectation. The study of Dell'Ariccia, et al. (2012) also found a similar result. One can therefore safely say that NPL depends on the long run equilibrium of the combination among the three variables (GAP, INF and UMP).

b) Short-Run Results Model One

The coefficient of the error correction term (ECT) which is the long term combination of all the variables is on the lower panel of Table 5.3 is negative and statistically significant at 10 percent level of significance. This means that with a 95 percent confidence interval, in the long run, GAP, INF and UMP are significantly affecting NPL. This also implies that in the case of any misalignment within the system in the short run, there will be a convergence in the long run. The ECT coefficient of -0.033 which reflects the period of which NPL will return to equilibrium, therefore implies that 3 percent deviation in the previous month is corrected in the current month. This means that it might take up to 33 months for NPL to return to equilibrium if it deviates from the regression line. The short run coefficient s of the variables is not statistically significant.

5.3.3.2 PMG Estimate for Model Two

The PMG (Panel ARDL 2 1 0 2 0 2 0 2) estimation result for the impact of financial indicators on credit risk is presented in Table 5.4. The indicators include stock market index (SID), interbank rate (IBR) and real exchange rate (EXR).

Table 5. 4: Panel ARDL Result Model Two (dependent variable NPLs)

	Model Two Pooled mean group estimation						
	Long Run Coefficients						
	NPL	Coef.	Std.	Err.	z P>z	[95%	Conf.Interval]
ECT							
	SID	4.934964	1.847091	2.67	0.008*	1.314732	8.555196
	IBR	3.211207	0.521997	6.15	0.000*	2.18811	4.234303
	EXR	-3.27762	2.060253	-1.59	0.112	-7.31564	0.760406
SR	**Short Run**						
	ECT	-0.00934	0.003202	-2.92	0.004*	-0.01562	-0.00307
	SID						

	D1.	-0.28132	0.182475	-1.54	0.123	-0.63896	0.07633
	IBR						
	D1.	-0.01555	0.005787	-2.69	0.007*	-0.02689	-0.00421
	EXR						
	D1.	29.73452	15.92568	1.87	0.062***	-1.47925	60.94829
	_cons	-0.62063	0.141831	-4.38	0.000	-0.89861	-0.34264
Hausman Test	chi2(3)	=	(b-B)'[(V_b-V_B)^(-1)](b-B)				
	chi2(3)		0.85				
	Prob>chi2 =	0.8383					

Source: Estimation.
*, **, *** means significance at the 1 percent, 5 percent and 10 percent level of significance respectively

a) Long-Run Results Model Two

The long run estimates are presented in the upper panel while that of the short run are presented in the lower panel of Table 5.4. The result shows that EXR although negative but does not have a significant impact on NPL in the long run. Furthermore, SID and IBR also exhibited a significant relationship with NPL at the 1 percent significance level although positive. According to Jimenez et al. (2013) and Ramcharan and Crowe (2013), an increase in the interest rate will lead to an increase in NPLs, although Crook and Banasik (2012), opined that the impact of IBR on NPL depends on how it is included in the modelled. There will be a positive relationship between the two variables if NPL is taken from time"t", but if it is taken from time"$t-1$", there will be a negative relationship. This stance was also supported by Dell'Ariccia et al. (2012). They concluded that reductions in interest rates increase NPLs as a result of relaxing the conditions for granting mortgages, leading to growth in credit and more loan defaults (Dell'Ariccia, et al., 2012).

b) Short-Run Results Model Two

The short run result for the financial risk model is presented in the lower panel of Table 5.4. As seen, the coefficient of the error correction term (ECT) which is the long term combination of all the variables is negative and highly statistically significant at 1 percent level of significance since the p-value of 0.004 is less than 0.05. This means that the short-run dynamics are thus reinforcing the model towards equilibrium in the long-run and that with a 95 percent confidence interval, in the long run, SID, IBR and EXR are significantly affecting NPL. This also implies that in the case of any misalignment within the financial system in the short run, there will be a long run convergence back to equilibrium. The ECT coefficient of -0.009 which reflects the period of which NPL will return to equilibrium, therefore implies that 0.9 percent deviation in the previous month is corrected in the current month. This means that it might take up to 111 months (9.25 years) for NPL to return to equilibrium if it deviates from the regression line, though it is fairly slow. The short run coefficient s of the variables is not statistically significant. The coefficients of IBR and EXR are all significant at the 1 percent and 10 percent significance level respectively with.

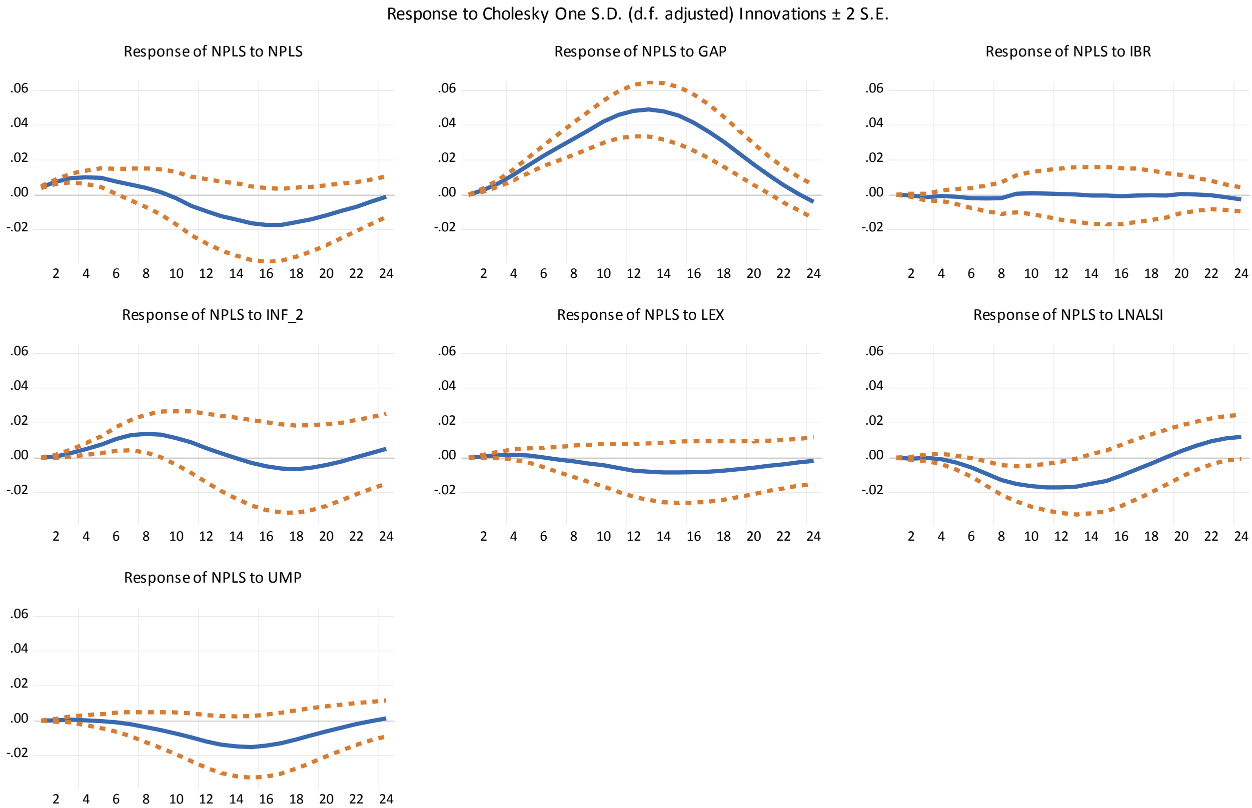
5.3.4 MACRO STRESS TESTING

To complement the multivariate analysis above and identify the transmission of macroeconomic shocks, a VAR model is employed. The VAR estimation is done on country bases so as to identify country-specific characteristics. The dynamic behaviour of the model is assessed using impulse response functions (IRF). The IRF describes the reaction of one variable in the system to innovations in another variable in the system while holding all other shocks at zero. The shocks in the VAR were orthogonalized using Cholesky decomposition, which implies that variables appearing earlier in the ordering are considered more exogenous, while those appearing later in the ordering are considered more endogenous. The Impulse IRF graphs for each of the countries are presented in sections 5.3.4.1-5.3.4.4.

5.3.4.1 EGYPT Test

The response of NPLs to sudden shock from macroeconomic and financial factors such as; output gap, interbank rate, inflation, exchange rate unemployment and stock market index for the Egyptian economy. The IRF result is presented in Figure 5.1.

a) Impulse Response Function

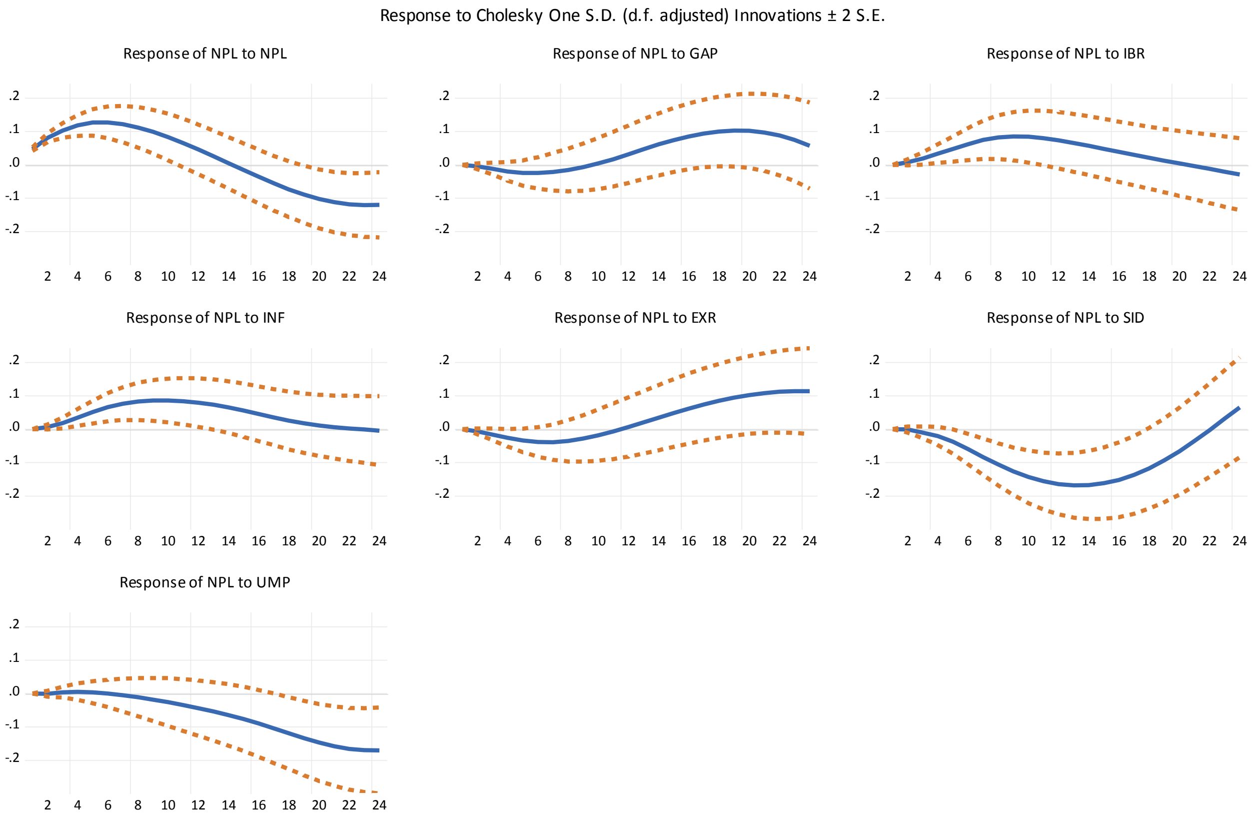


Source: Estimation

Figure 5. 1: Response of NPLs to a one S.D shocks in other variables for the Egyptian Economy

Based on the IRF graph presented in Figure 5.1, NPL responds positively to a GAP (the response lasts 1-23 months) and INF (the response last for 1-13 months) for the Egyptian economy, while it responded negatively to a one S.D shock in SID, UMP and EXR. One standard shock to GAP and INF leads to a cumulative increase of 0.29 percentage point and 0.09 in NPLs, respectively in the first 12 months. For most of the period, the response of NPL to a shock in IBR was not profound all through the period.

5.3.4.2 KENYA

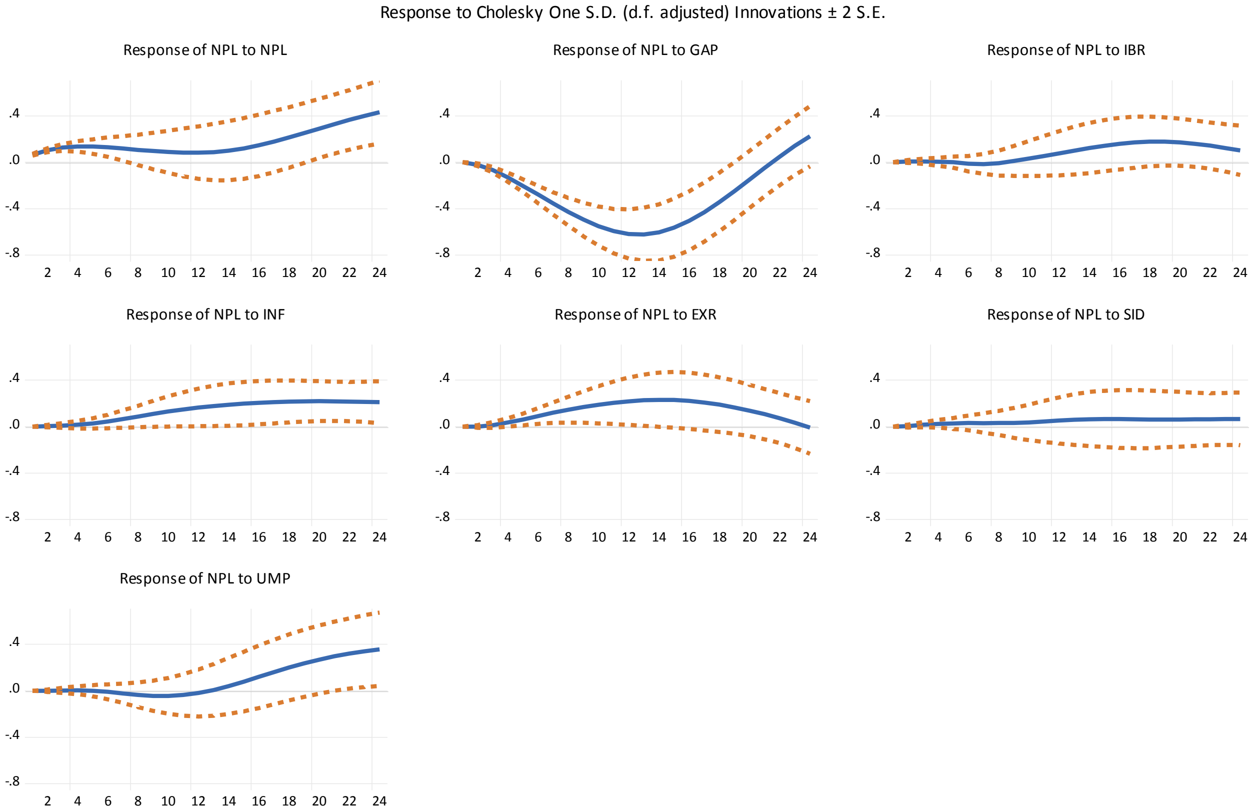


Source: Estimation

Figure 5. 2: Response of NPLs to a one S.D shocks in other variables for the Kenyan Economy

Based on the IRF graph presented in Figure 5.2, NPL responds positively to a shock in INF for the Kenya economy, while it responded negatively to a 1 S.D shock in GAP (3^{rd} to 9^{th} month), EXR, SID and UMP after the first 2 months. One standard shock to INF leads to a cumulative increase of 0.67 percentage point in NPLs in the first 12 months. On the other hand, a one S.D shock to IBR leads to a positive response in NPL up to the 20^{th} month before becoming negative.

5.3.4.3 NIGERIA

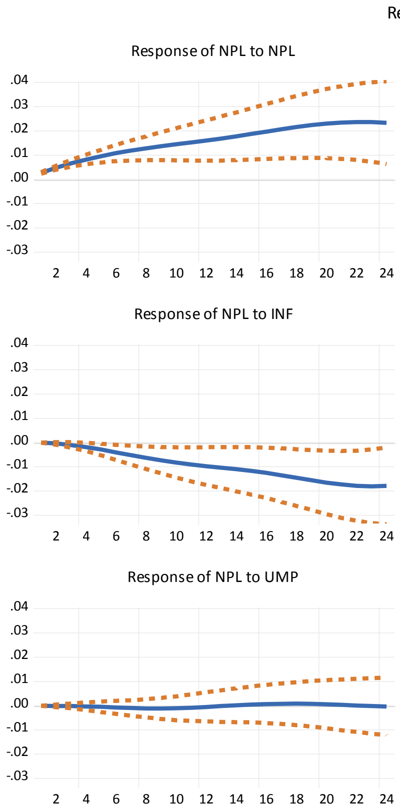


Source: Estimation

Figure 5. 3: Response of NPLs to a one S.D shocks in other variables for the Nigerian Economy

Based on the IRF graph presented in Figure 5.3, NPL responds positively to a shock in INF and UMP for the Nigerian economy. As inflation rises, the purchasing power of consumer falls which in turn reduce their disposable income. This will mean that nonperforming loans will rise as they will have less money or income to pay back loans. The same goes for unemployment. A shock to unemployment tends to lead to increasing nonperforming loans due to the fact that there would be no income or funds to pay back their debts. It also responded positively to the IBR, EXR and SID although the response to shock in SID was not profound all through the period. On the other hand, it responded negatively to a 1 S.D shock in GAP (2nd to 22nd month). This means an innovation or positive shock to output gap equal to one standard deviation, ceteris paribus, resulted in a persistent reduction in nonperforming loans. The result is plausible as output increases, employment rises which in turn reduce bad debts.

5.3.4.4 SOUTH AFRICA



Source: Estimation

Figure 5. 4: Response of NPLs to a one S.D shocks in other variables for the South African Economy

Based on the IRF graph presented in Figure 5.4, NPL responds positively to a IBR (the response lasts for the whole period) and EXR (the response last for the whole period although it converges back to equilibrium at the end of the period) for the South African economy. The result further revealed that for the accumulated responses over a two year (24 months) period, an innovation or positive shock to output gap equal to one standard deviation, ceteris paribus, resulted in a persistent reduction in nonperforming loans. On the other hand, it responded negatively to a one S.D shock in INF and GAP. In the case of a shock from UMP and SID, the response is not pronounced for almost all the period.

5.4 CHAPTER SUMMARY

This chapter assessed and analyzed the vulnerabilities of financial systems to credit risk through stress testing. Stress tests in the financial sector provide information on a system's potential losses under exceptional but plausible shocks; thereby assisting policymakers assess the significance of the system's vulnerabilities. Credit risk was measured by the ratio of non-performing loans to total loans. Several methods have used to assess the vulnerabilities of the financial system to credit risk and they include value at risk (VaR), expected shortfall (ES), vector autoregression (VAR), and global vector autoregression (GVAR) among others. A two-step approach was adopted in this study and they include the panel ARDL and vector autoregression. The panel ARDL was used to determine the drivers on credit risk using the PMG estimation technique. The PMG estimation technique was selected instead of the MG based on the Hausman test and it is believed to be more efficient.

The macroeconomic drivers of credit risk were assessed using a panel ARDL model. The estimation was divided into two namely: the macro model and financial model. From the estimation, it was evident that all the variables under both the macro and financial model jointly determine credit risk, although when examined on an individual basis only, UMP, IBR, and INF have a significant impact on NPL in the long run. Although EXR does not significantly affect NPL in the long run, it was, however, significant in the short run.

Turning to the macro stress testing, the VAR methodology was employed to stress test the emerging African economy financial sector and the result indicated that there a significant relationship between changes in output gap (GAP) and the nonperforming loans. This is similar to the study conducted by the Bank of Japan (2009), Bank of Ghana (2006) and Bank of England (2005) Vazquez et al. (2012), as well as Jordan and Tucker (2013). The result further revealed that for the accumulated responses over a two year (24 months) period, an innovation or positive shock to output gap equal to one standard deviation, ceteris paribus, resulted in a persistent reduction in nonperforming loans for South Africa and Nigeria. It is believed that growth in output tends to increase employment thereby reducing nonperforming loans. Significant relationships were also established between inflation and nonperforming loans. In all, South Africa and Nigeria's financial system seems more resilient to credit losses associated with this scenario without threatening financial stability compared to Kenya and Egypt.

CHAPTER SIX

ASSESSING THE DRIVERS OF CAPITAL FLOWS IN EMERGING AFRICAN ECONOMIES

This study examines the sources and effects of capital flows and their surges on macroeconomic variables. The chapter is divided into 5 sections. Section one gives a brief background of capital flows and the global financial crisis. This is followed by the theoretical framework and methodology in Section two. Data and data sources were highlighted in Section 3, while the estimation result is presented in Section Four. A chapter summary is presented in the last Section.

6.1 GLOBAL FINANCIAL CRISIS (GFC) AND CAPITAL FLOW

In the aftermath of the Global Financial Crisis (GFC), a good number of central banks have incorporated major adjustment in their oversight function in terms of ensuring financial stability (Baskaya, et al. 2016). It is evident that part of the reason for the increase in capital flows into emerging markets was as a result of the unconventional policies implement by most developed economies. These policies led to a high level of global liquidity and a low-interest rate in these countries (Baskaya, et al. 2016). Capital flows may generate overheating, excessive credit creation and asset price bubbles, loss of competitiveness due to currency appreciation, and increased vulnerability to the crisis (Cardarelli, Elekdag, and Kose 2010; Tillmann, 2013; Forbes and Warnock 2012).

These inflows, mostly in the form of portfolio inflows, have in turn led to risks associated with a massive domestic credit expansion in emerging market economies (EMEs). These phenomena have thus raised concerns over potential external imbalances, as well as risk to macroeconomic and financial stability. Although, some countries with some degrees of financial openness are able to share income risks with rest of the world and bridge saving-investment and foreign exchange gaps (Prasad et al., 2003; Akinboade, Siebrits and Roussot, 2006; Alley, 2017), such countries are also confronted with the risks of having their economies exposed to exogenous shocks transmitted through capital flow volatility which, in turn, induce domestic financial instability (Kaminsky, 2005; Fernandez et al., 2015) thereby slowing down growth.

To address this risk, central banks and policymakers have turned their attention to macroprudential policy measure as a complement to monetary policy. One major lesson learnt in the aftermath of the GFC is that ensuring macroeconomic stability is not a sufficient condition for financial stability. For example, before the GFC, financial imbalances built up in advanced economies notwithstanding stable growth and low inflation. Also, microprudential regulation and supervision, which is aimed at ensuring safety and soundness of individual financial institutions, turned out to be insufficient, as system-wide risks could not be contained. Another challenge faced by policymakers on the debate for the implementation of macroprudential policy is whether it should be independent or set by the central banks in line with monetary policy decisions to ensure financial stability (Alberola et al., 2011; Vermandel, 2014). While there is a high level of awareness of the contribution of monetary policy to financial stability, its role is in practice limited (Alberola et al., 2011). A loose monetary policy may amplify the financial cycle or, conversely, a macroprudential policy that is too restrictive may have detrimental effects on credit provision and hence on monetary policy transmission. Where low policy rates are consistent with low inflation, they may still contribute to excessive credit growth and to the build-up of asset bubbles and induce financial instability (Vermandel, 2014).

According to Vermandel (2014), “the main argument in favour of mixing both monetary and macroprudential policies is the following: to the extent that MPP reduces systemic risks and creates buffers, it helps the task of monetary policy in the face of adverse financial shocks while the argument against lie in its potential conflict of interest, or at least trade-offs, between the two policies”.

6.2 THEORETICAL FRAMEWORK AND METHODOLOGY

This study, therefore, employs the panel structural vector autoregression (PSVAR) to identify the sources of fluctuation within the financial system. The approach was chosen due to the fact that it is more flexible to allow the recovery of interesting pattern with little or no theoretical background (Graeve and Karas, 2010), especially in a financial or banking related studies. Also, the advantage of panel vector autoregression (PVAR) to combine past, present and future events in a study make it more efficient other methods such as the ordinary least squares (OLS) and generalized method of moments (GMM) (Canova and Ciccarelli, 2014; Akande, 2018). The

PSVAR was estimated using eight endogenous variables, namely; RGDP, INFR, INTR, CRGT, EXPR, UMP, EXHR, BMSP and one exogenous variable, namely, FDI as proxy for monetary and capital flow shock.

Assuming that the emerging African economies are represented with the following structural panel equation:

$$EY_{it} = \alpha_{io} + \beta_1 Y_{it-1} + \beta_2 Y_{it-2} + \beta_3 Y_{it-3} + \cdots + \beta_n Y_{it-n} + \ni X_t + V\varepsilon_{it} \qquad (1)$$

where E is the $K\ x\ K$ matrix describing the contemporaneous relationship among the variables. Y_{it} is a $K\ x\ 1$ vector of endogenous variables such that $Y_{it} = Y_{1t}, Y_{2t}, Y_{3t} \ldots, Y_{nt}$. α_{i0} is a $K\ x\ 1$ vector of constant representing country specific intercepts, while $\beta_1, \beta_2, \beta_3, \ldots, \beta_n$ are $k\ x\ k$ matrix of the coefficient of lagged endogenous variables respectively. $\ni$ and X_t are the vectors of coefficients and the exogenous variables that captures the external shocks, while V represents a KxK matrix with a zero diagonal element which allow for direct effects of some shocks on more than one endogenous variables in the system, ε_{it} ia a vector of uncorrelated error terms.

Due to the feedback inherent in the VAR and SVAR process (see Enders 2004, 2008), the PSVAR cannot be estimated directly using Equation (1). The structure of the system incorporates feedbacks which makes it difficult to estimate due to the fact that the endogenous variables are allowed to affect each other in the current and past realization time path of EY_{it}. However, the information in the system can be estimated and recovered by estimating a reduced-form SVAR implicit in the equations (see Ngalawa and Veigi, 2011). By multiplying equation (1) by the E^{-1}gives:

$$Y_{it} = E^{-1}\alpha_{io} + E^{-1}\beta_1 Y_{it-1} + E^{-1}\beta_2 Y_{it-2} + E^{-1}\beta_3 Y_{it-3} + \cdots + E^{-1}\beta_n Y_{it-n} + E^{-1}\ni X_t + E^{-1}V\varepsilon_{it} \qquad (2)$$

Simplifying equation 2, we denote $E^{-1}\alpha_{io} = K_i$, $E^{-1}\beta_1 \ldots E^{-1}\beta_n = L_1 \ldots L_n$, $E^{-1}\ni = \emptyset$ $E^{-1}V\varepsilon_{it} = \mu_{it}$

Therefore, equation 2 can be expressed as:

$$Y_{it} = K_i + L_1 Y_{it-1} + L_2 Y_{it-2} + L_3 Y_{it-3} + \cdots + L_n Y_{it-n} + \emptyset X_t + \mu_{it} \qquad (3)$$

It must be noted that Equation 3 differs from equation 1 in the sense that equation 1 is referred to as the P-SVAR or primitive system where all the variables have contemporaneous effects on each other, while equation 3 is referred to as the condensed form P-SVAR where all the right-hand side (RHS) variables are predetermined at time t and none of the variables has a direct contemporaneous (immediate) effect on another in the model.

Additionally, the error term μ_{it} is composite shocks in Y_{it} (Enders, 2008). Therefore, the condensed form of the P–SVAR from equation 3 can be rewritten as:

$Y_{it} = K_i + L(B)Y_{it} + J(B)X_t + \mu_{it}$ (4)

Where Y_{it} and X_t are a $nx1$ vector of variables given by

$Y_{it} = (RGDP, INFR, INTR, CRGT, EXPR, UMP, EXHR, BMSP)$ (5)

$X_t = (FDI)$ (6)

Where Equation 5 is a vector of endogenous variables for the emerging African economies used in the study and equation 6 is the vector of an exogenous variable that controls for external shocks. K_i is the vector of constant representing country specific intercept, while $L(B)$ is the matrix of polynomial in the lag operator that captures the relationship between the endogenous variables and their lags. $\mu_{it} = E^{-1}V\varepsilon_{it}$ is a vector of random disturbances, which can as well be specified as $E\mu_{it} = V\varepsilon_{it}$ when you multiply both sides by E.

To recover the information in the structural model, we impose restriction in the matrix $E \; and \; V$ in the system, as contained in Equations (7) as follows. The identification scheme follows Kutu and Ngalawa (2016) as well as Akande and Kwenda (2017), whereby structural restrictions are applied to the contemporaneous parameter matrix.

$$
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\varphi_{21} & 1 & \varphi_{23} & \varphi_{24} & \varphi_{25} & 0 & 0 & 0 & 0 \\
\varphi_{31} & \varphi_{32} & 1 & 0 & 0 & \varphi_{36} & 0 & \varphi_{38} & 0 \\
\varphi_{41} & \varphi_{42} & 0 & 1 & 0 & 0 & 0 & 0 & \varphi_{49} \\
\varphi_{51} & \varphi_{52} & 0 & \varphi_{54} & 1 & \varphi_{56} & 0 & 0 & \varphi_{59} \\
\varphi_{61} & \varphi_{62} & 0 & 0 & 0 & 1 & \varphi_{67} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & \varphi_{78} & 0 \\
\varphi_{81} & 0 & 0 & 0 & 0 & 0 & 0 & 1 & \varphi_{89} \\
\varphi_{91} & \varphi_{92} & \varphi_{93} & \varphi_{94} & \varphi_{95} & \varphi_{96} & \varphi_{97} & \varphi_{98} & 1
\end{bmatrix}
\begin{bmatrix}
\varepsilon_t^{fdi} \\ \varepsilon_t^{rgdp} \\ \varepsilon_t^{intr} \\ \varepsilon_t^{infr} \\ \varepsilon_t^{umpr} \\ \varepsilon_t^{bmsp} \\ \varepsilon_t^{cgdp} \\ \varepsilon_t^{expr} \\ \varepsilon_t^{exhr}
\end{bmatrix} =
$$

$$
\begin{bmatrix}
b_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & b_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & b_3 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & b_4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & b_5 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & b_6 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & b_7 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & b_8 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & b_9
\end{bmatrix}
\begin{bmatrix}
\mu_t^{fdi} \\ \mu_t^{rgdp} \\ \mu_t^{intr} \\ \mu_t^{infr} \\ \mu_t^{umpr} \\ \mu_t^{bmsp} \\ \mu_t^{cgdp} \\ \mu_t^{expr} \\ \mu_t^{exhr}
\end{bmatrix} \qquad (7)
$$

where RGDP is Real gross domestic product and it's the proxy for economic activity, INFR is the inflation rate, INTR is the interest rate, CRGT is the credit growth which is proxied by credit to the private sector, EXPR is the export rate, UMP is the unemployment rate, EXHR is the exchange rate, BMSP is the broad money and one exogenous variable FDI. All variables are expressed in percentages.

The first matrix on theleft-hand side of the system Equation (7) is the B matrix, which relates to the non-recursive restriction in the model, while the first matrix on the right-hand side indicates the H-matrix, also known as the diagonal matrix. The terms $\varepsilon_t^{fdi}, \varepsilon_{it}^{rgdp}, \varepsilon_{it}^{intr}, \varepsilon_{it}^{infr}, \ \varepsilon_{it}^{umpr}, \varepsilon_{it}^{bmsp}, \varepsilon_{it}^{cgdp}, \varepsilon_{it}^{expr}$ $and\ \varepsilon_{it}^{exhr}$ are the residuals in the reduced-form disturbance to both the external and domestic variables and further represent the unexpected movements of each variable, and

$$\mu_t^{fdi}, \mu_{it}^{rgdp}, \mu_{it}^{intr}, \mu_{it}^{infr}, \mu_{it}^{umpr}, \mu_{it}^{bmsp}, \mu_{it}^{cgdp}, \mu_{it}^{expr} \text{ and } \mu_{it}^{exhr}$$

are the structural shocks associated with the respective equations.

This study relied on Amisano and Giannini (1997) for the identification of the scheme, whereby the PSVAR requires $2n^2 - n(n+1)/2$ or 70 restrictions on the E and V matrices jointly where n is the number of variables. Since V is assumed to be a diagonal matrix, 72 exclusion restrictions are imposed on it whereas 45 restrictions are required to be imposed on the E matrix for the system to be exactly identified. Since our non-recursive $P{-}SVAR$ imposes 42 zero restrictions on E, the system is over-identified and 30 free parameters in the E matrix and 9 in the V matrix have to be estimated (see system of Equations 7). The pattern whereby the variables influence each other is based on economic theory and also depends on their position in the identification scheme.

6.3 DATA

Monthly data for African emerging economies from 2006m1-2017m12 was used. Data which include real gross domestic output (rgdp), inflation rate (infr), real interest rate (intr), Credit growth (crgt), export (expr), exchange rate (exhr), broad money supply (BMSP), foreign direct investment (FDI) were obtained from the world development indicators (World Bank, 2019). Since the data retrieved was an the annual series, I transformed it into higher frequencies of a monthly basis (See Kutu and Ngalawa, 2016; Akande and Kwenda, 2017).

6.4 ESTIMATION RESULT

The result of the estimation is presented in this section. The impact of capital flow surge on macroeconomic variables is illustrated using the impulse response function (IRF) and historical decomposition. First, the lag length was selection criteria and panel unit root test are presented in Sections 6.4.1 and 6.4.2 respectively, while the analysis of the IRF for one standard deviation shock to the errors and VDC are presented in Sections 6.4.3 and 6.4.4 respectively.

6.4.1 Lag length test

The study tests for various lag lengths employing the various lag selection criteria to allow for adjustments in the model and the attainment of well-behaved residuals. The standard Akaike Information Criteria (AIC), Final Prediction Error (FPE), Sequential Modified LR, Schwarz Information Criterion (SC) and Hannan-Quinn information criterion (HQ) suggested an optimal 4-lag length for the $P{-}SVAR$. The choice of the 4-lags by this study offers accurate and more robust dynamics without necessarily shortening the estimation sample too much, which would compromise the degrees of confidence (See Table 6.1). This lag length also allows for no serial correlation in the residuals. The study is also further guided by previous studies by Sharifi-Renani (2010), Elbourne (2008) and Kutu and Ngalawa (2016) who also utilized 4-lags in their study.

Table 6. 1: Lag Length Selection Criteria

VAR Lag Order Selection Criteria						
Endogenous variables: FDI RDGP INFR EXHR BDSP INTR EXPR CGRT UMP						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-12076.3	NA	44938189	43.16169	43.23125	43.18885
1	3640.271	30871.78	2.52E-17	-12.6795	-11.984	-12.4079
2	10170.3	12616.95	2.50E-27	-35.7118	-34.3902	-35.1958
3	13101.96	5570.155	*9.49E-32*	-45.8927	-43.9452	-45.1323
4	13951.46	1586.741*	6.10e-33*	-48.63736*	-46.06379*	-47.63245*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Source: Estimation

6.4.2 Panel Unit Root Test

This study applies the Levin, Lin and Chu (LLC) and Im, Pesaran and Shin (IPS) unit root tests. The result indicates that they are of the same order I(1). The results of the panel unit root tests for the variables can be found in the appendix (See Appendix 2.1). The model also passed the entire diagnostic test conducted. The test included the VAR Residual Heteroskedasticity Tests as well as the VAR Residual Serial Correlation LM Tests (See Appendix 2.1).

6.4.3 The Impulse Response Analyses

This subsection analyses the response of macroeconomic variables to a one standard deviation shock in capital flows. Impulse response function provides information on the future states of the economy as it relates to the variables in the system where there are changes in any of the components. In order words, the impulse response function (IRF) traces the response of the endogenous variable to its own shocks and to shocks in every other endogenous variable. In other words, it is the path whereby the variables return to equilibrium after any shock in the system (William, 2000).

6.4.3.1 Macroeconomic Variables to Capital Flow Shocks

The result as presented in Figure 6.1 indicate the impulse responses of macroeconomic variables to a one standard deviation shock in capital inflows which was proxied by FDI. The result shows that a shock from capital flows raises output for the entire 60months time horizon. A capital flow shock first causes a decline in inflation rate for the first 13 months thereafter it increases over a significant period of time before it converges back to equilibrium. Inflation is a major factor that determines the level of FDI in a particular country. According to Macpherson, (2013), a high rate of inflation signifies economic instability associated with inappropriate government policies; distort economic activities, thereby leading to a lesser capital inflow (Khan and Mitra, 2014). Export also exhibited the same trend shown by a shock to the inflation rate. In the case of unemployment, the result shows that capital flow shock led to a decline in the unemployment rate.

This is in line with economic theory, which suggests that as FDI increases, unemployment should fall, all things being equal (Irpan, et al. 2016).

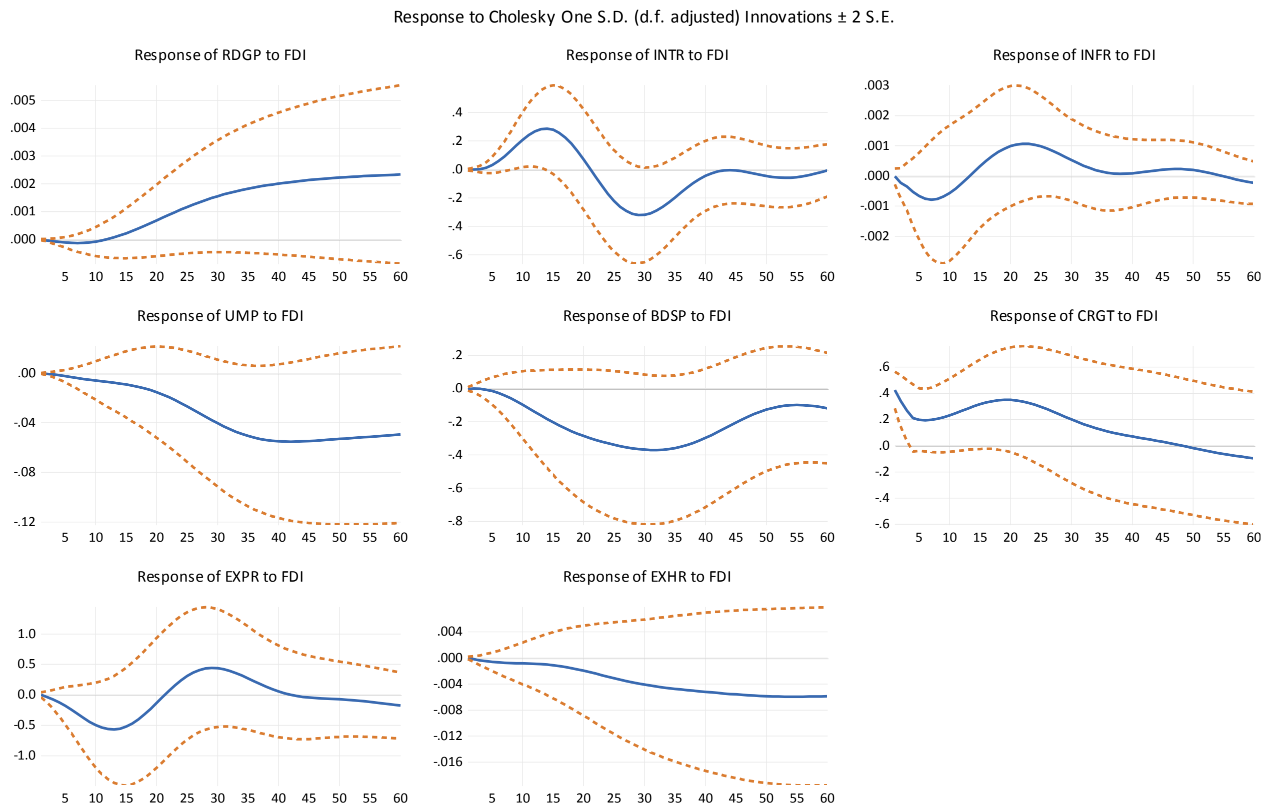


Figure 6. 1: Impulse Response function

The result is plausible as most FDIs come in the form of aid, grant, remittance which may be due to the high level of unemployment in most emerging African economies. Turning to the exchange rate, FDI responds negatively all through the period. This result is supported by the study of Korinek and Sandri, 2016 the level of the exchange rate can amplify the shocks because it influences how much foreign lenders value domestic collateral. That is to say, high fluctuations in the domestic currency market tend to affect the movement of capital flows into the economy.

6.4.3.2 Variance Decomposition

This Variance decomposition (VDC) helps in examining the effect of the impulses on the explained variables. It indicates the extent to which the forecast error variance of each variable can be explained by shocks exogenous to the remaining variables. According to Ziegel and Enders (1995), variance decomposition accounts for the information about the proportion of the movements in a sequence that are due to the shock in the variable itself and other shocks identified.

Table 6. 2: Variance Decomposition

Period	S.E.	FDI	RDGP	INFR	EXHR	BDSP	INTR	EXPR	CGRT	UMP
1	0.353529	100	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.476047	99.58566	0.016715	0.101737	6.83E-05	0.007639	0.003466	0.122875	0.03656	0.125283
3	0.557721	98.76349	0.059613	0.358086	0.000051	0.008584	0.00263	0.250776	0.116589	0.440179
4	0.6189	97.6181	0.103603	0.661954	0.001257	0.014136	0.002531	0.39482	0.230366	0.973236
8	0.786389	92.25138	0.138583	1.730818	0.028741	0.06817	0.005932	0.690926	0.298645	4.786805
9	0.816864	90.93332	0.128807	1.90315	0.036544	0.087652	0.005553	0.687867	0.295179	5.921927
10	0.844281	89.71957	0.128273	2.035839	0.042643	0.107351	0.006331	0.664109	0.28817	7.007708
11	0.869009	88.63865	0.144839	2.132927	0.046597	0.125891	0.009342	0.630703	0.278765	7.992286
12	0.891336	87.70457	0.184738	2.199054	0.048349	0.141958	0.014894	0.599874	0.268137	8.83843
13	0.91151	86.91749	0.252202	2.238916	0.048221	0.1544	0.022318	0.583486	0.257357	9.52561
14	0.929769	86.26563	0.349349	2.256923	0.046874	0.162417	0.030169	0.591672	0.247391	10.04958
20	1.011348	83.84987	1.43613	2.105847	0.073683	0.162289	0.043902	1.308421	0.234463	10.7854
21	1.021902	83.48451	1.65428	2.064502	0.093641	0.180882	0.054969	1.495139	0.239342	10.73273
22	1.031898	83.09075	1.867022	2.024786	0.119369	0.217033	0.077165	1.677186	0.244494	10.68219
23	1.04142	82.661	2.069369	1.988489	0.150482	0.275797	0.113035	1.846031	0.249034	10.64676
24	1.050553	82.18861	2.257389	1.957146	0.186162	0.361551	0.16371	1.995082	0.252205	10.63815
25	1.05939	81.66722	2.428318	1.932048	0.225216	0.477496	0.228718	2.120043	0.253509	10.66743
26	1.06803	81.09097	2.580561	1.914267	0.266181	0.62524	0.306086	2.218949	0.252793	10.74495
27	1.07657	80.45539	2.713637	1.904673	0.307447	0.804505	0.392684	2.291943	0.250299	10.87942
28	1.085095	79.75876	2.828067	1.903947	0.347405	1.013014	0.484726	2.34087	0.246665	11.07654
29	1.093662	79.00347	2.925234	1.91258	0.384602	1.246601	0.578337	2.368777	0.242865	11.33754
30	1.102297	78.19692	3.007214	1.93085	0.41786	1.499535	0.670053	2.37939	0.240104	11.65807
40	1.176773	70.81855	3.591844	2.491591	0.51761	3.735985	1.313945	2.20161	0.465725	14.86314
50	1.208152	68.12071	4.491935	2.714552	0.49796	4.223284	2.087005	2.117358	1.019696	14.7275
60	1.224378	66.6719	4.945175	2.669464	0.48716	4.194818	2.759594	2.073349	1.653526	14.54501
Cholesky Ordering: FDI RDGP INFR EXHR BDSP INTR EXPR CGRT UMP										

Source: Estimation

Specifically, the variance measures the cumulative fluctuations over different horizons in the forecast error of changes in the capital flows proxy. The framework that was adopted in this study gives the opportunity to trace out the effects of various shocks of the capital flows to emerging African economies. The result as presented in Table 6.2 indicates that that own shock is the major source of variation in the model. Overall, export and unemployment shocks appear to explain largely the variations in foreign direct investment. In particular, it appears that variations in the foreign direct investment are explained primarily by shocks to export and unemployment both in the medium- to longer- term horizons.

Therefore, for foreign direct investment, shocks on export and unemployment seem to be consistently dominant across various time horizons, suggesting that real variables rather than monetary variables are the key drivers of capital flows to emerging African economies. This may be because most of the FDI come in the form of aids, remittance and donations which is partly due to the high level of unemployment in most of the emerging African economies.

6.5 CHAPTER SUMMARY

It is clear that capital flows into emerging markets have surged since after the GFC. These inflows which are majorly in the form of portfolio inflows constitute a great risk to the real economy in the form of massive domestic credit expansion in the emerging market. These phenomena have thus raised concerns over potential external imbalances, as well as risk to macroeconomic and financial stability. Capital flows surge has the potential of generating overheating, excessive credit creation and asset price bubbles, loss of competitiveness due to currency appreciation, and increased vulnerability to crisis. This study employed a $P{-}SVAR$ to investigate the source capital flow surge within the system. Monthly data from 2006m1 to 2017m12 was used. The result shows that capital flow, which is proxied by FDI, is influenced by a wide variety of macroeconomic variables. Furthermore, the result of the data analysis indicates that inflation seems to have a similar impact on FDI than exchange rate; thus maintaining inflation stability could ensure economic stability and in turn, stimulate FDI. FDI responds positively to growth in real gross domestic product. For the exchange rate, it was clear that high fluctuation in the exchange rate has a great influence on the movement of capital flows into the emerging African economies. This is because the result revealed that a shock or innovation to the exchange rate leads to a deterioration in capital flows. This result is similar to the findings of Agénor et al., (2014) who opined that exchange rate depreciation can be linked to decline external funding conditions during crisis period. This according to Agenor et al. (2014) has great implication for financial stability in a number of ways. To start with, high fluctuations in currency can disrupt exchange rate expectation, which, in turn tend, lead to changes in capital flows. Also, the level of exchange rate can propagate the level of shock within the system due to the fact that it influences the value placed by the foreign lender on domestic assets (Korinek and Sandri, 2016). This will further lead to a deterioration of the exchange rate. Furthermore, other major drivers of FDI to emerging African economies include export growth and unemployment.

CHAPTER SEVEN

MEASURE SYSTEMIC RISK IN EMERGING AFRICAN ECONOMIES

This chapter focuses on identifying and measuring the sources of systematic risk and its impact on the stability of the financial system. It is important to study risk spill over as well as capturing systemic risk through the VaR of an institution conditional on other institutions in distress. This will be of help to central bank authorities so that they can formulate policies that mitigate such risks. The chapter is divided into 5 sections. Section 1 gives a background of systemic risk measurement, while the theoretical framework and methodology is presented in Section 2. The data used in the study and the results and discussions are presented in Sections 3 and 4 respectively. The chapter summary is given in Section 5.

7.1 SYSTEMIC RISK MEASUREMENT

The high level of interconnectedness of the global financial market was brought to the fore after 2007/08 GFC. In addition to that, it was also clear that financial risk from an institution can spread rapidly through the financial system, thereby threatening the stability of the financial system and by extension negatively affecting the entire global economy. However, Brunnermeier and Pedersen (2009) argued that the degree to which international financial institutions are linked depends on the level of market liquidity. Clearly, banks play a crucial role in the proper functioning of an economy since they provide the necessary liquidity to the markets and help to promote economic growth (Drakos, 2014). A distressed bank or banking sector can be systemic as it may serve as a potential source of financial crisis and instability to the system.

Systemic risk was first measured using the Credit Default Swaps (CDS) and applying the principal component analysis (PCA). The CDS are financial instruments that provide insurance against the risk of a counterparty default, which may be a company or a country (Jemaa, 2015). The first principal component generated from the CDS spreads is generally believed to be the source of systemic risk since it represents the common factors influencing the CDS. After this, the difference between the interbank rates (LIBOR) and overnight index swaps (OIS) (LIBOR-OIS spreads) was used to reflect the liquidity and default risk in the system. The LIBOR is the interbank rate while the OIS is the overnight index swap.

Other methods includes the use of probability of default of banks since its linked to the value of bank assets and debts (Lehar, 2005), value-at-risk (VaR) (Adrian and Brunnermeier, 2011), collateralized debt obligation (CDOs), Systemic Expected Shortfall (SES) (Achraya et al. 2010; Lahmann and Kaserer, 2011), Marginal Expected Shortfall (Achraya et al. 2010; Brownlees and Engle, 2011), as well as the PCA and Granger-causality networks (Billio et al. 2012). However, Adrian and Brunnermeier (2011) developed a new approach to measure systemic risk. This is the Conditional Value at Risk (CoVaR) which centres on the transmission of risk from individual banks to the whole system.

7.2 THEORETICAL FRAMEWORK AND METHODOLOGY

Losses tend to spread across financial institutions during the financial crisis and thereby threatening the whole financial system (Adrian and Brunnermeier, 2011). This gives rise to systemic risk which adversely affects the supply of credit to the real economy. Systemic risk (defined as the probability of a given number of simultaneous bank defaults) measure captures the likelihood for the spreading of financial distress across institutions by gauging this increase in tail co-movement.

Several authors have tried to model systemic risk but have focused on the traditional measures which involve the use of bank balance sheet information such as non-performing loan ratios, earnings and profitability, liquidity and capital adequacy ratios. However, there have been growing efforts to measure the soundness of the financial system as a whole based on the information from the financial market due to the fact that balance sheet information is available at a relatively low frequency (quarterly) basis (Huang, Zhou, and Zhu, 2009). For example, Chan-Lau and Gravelle (2005), Chan-Lau (2010), Segoviano and Goodhart (2009) and Avesani et al. (2006) used the nth-to-default probability to measure the systemic risk by employing liquid equity market or credit default swap (CDS) market data with a modern portfolio credit risk technology (Huang et al., 2009). Acharya (2009), Adrian and Brunnermeier (2008) modelled systemic risk as to the correlation of returns on bank assets while Caruana (2010) examined systemic risk as a negative externality. The measurement of systemic risk using market-based data is advantageous in the sense that 1). They can be updated in a more timely fashion. 2). they are usually forward-looking, in that asset price movements reflect changes in market anticipation on the future performance of the underlying entities (Huang et al., 2009).

The most common measure of risk used by financial institutions is the value at risk (VaR). The VaR focuses on the risk of the individual financial institution (Adrian and Brunnermeier, 2011). However, individual institution risk may not necessarily reflect the risk inherent in the entire financial system. This study adopts the CoVaR model developed by Adrian and Brunnermeier (2011) to measure systemic risk. The CoVaR model is useful in studying risk spillovers as well as capturing systemic risk through the VaR of an institution conditional on other institutions in distress (Drakos and Kouretas, 2015). CoVaR as defined by Adrian and Brunnermeier (2011) as the $CoVaR_q^{j|i}$ as the VaR_q^j of institution j condition on some event $C(R^i)$ of institution i.

Where VaR_q^j is the q quantile, i.e.

$$P\left(R^j \leq VaR_q^j\right) = q \qquad (1)$$

The $CoVaR_q^{j|i}$ is the q^{th} quantile of the conditional probability distribution of return j

$$P\left(R^j \leq CoVaR_q^{j|C(R^i)} | C\left(R^i\right)\right) = q \qquad (2)$$

Where

R^j is the variable of institution j for which VaR_q^j is defined. It must be noted that VaR_q^j is typically negative although it switches in practice.

The contribution of institution j to that of i is denoted by

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^{j^i}} - CoVaR_q^{j|X^i=median^i} \qquad (3)$$

Where $CoVaR_q^{j|i}$ is the VaR of institution j' asset returns when institution the $i's$ returns are in a normal state of their distribution (e.g 50%), and $\Delta CoVaR_q^{j|i}$ is institution $j's$ VaR when institution $i's$ return are in an extreme bad condition. A good example of such is the recent financial crisis.

Furthermore, the $\Delta CoVaR_t^i$ for each institution is computed as follows:

$$\Delta CoVaR_q^{j|i)}(q) = CoVaR_q^{j|i)}(q) - CoVaR_q^{j|i)}(50\%) \qquad (4)$$

$$= \hat{\beta}^{j|i}[VaR_t^i(q) - VaR_t^i(50\%)] \quad (5)$$

However, in the case of systemic risk, $j = system$ i.e., when the return of the portfolio of all financial institutions is at it VaR level.

$$P\left(R^{system} \leq CoVaR_q^{system|C(R^i)} | C(R^i)\right) = q \quad (6)$$

Therefore,

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i=VaR_q^{i^i}} - CoVaR_q^{system|X^i=median^i} \quad (7)$$

In this case, $\Delta CoVaR_q^{system|i}$ denotes the difference between the VaR of the financial system conditional on the distress of financial institution i and the VaR of the financial system conditional on the median state of the institution i.

Although there are a number of estimation techniques that can be used to estimate $CoVaR$ such as GARCH, Expected Shortfall etc. This study adopted the Quantile regression to estimate the $CoVaR$. The methodology was developed by Koenker and Basset (1978) and extended by Koenker and Xiao (2002) and Koenker (2005). The method was used by Adrian and Brunnermeier (2011) to measure systemic risk within the financial system, Bernal, Gnabo, and Guilmin (2014) to measure the contribution of financial sector to systemic risk and Drakos and Kouretas (2015) to measure systemic risk within the real economy. The estimation will follow a six step procedure.

The first step deals with the modelling of returns R^ias a function of a set of state variables:

$$R_t^i = \alpha^i + \gamma^i M_t + \varepsilon_t^i \quad (8)$$

Where α^i is the constant, M_t is the vector of contemporaneous state variables and ε_t^i is the white noise error term which is assumed to be i.i.d with zero mean and constant variance and is also independent of M_t. The 1 percent quantile of market return based on quantile regression is then estimated.

In the second step, the predicted 1 percent Value-at-Risk for each segment of the financial sector is computed using the statistical variables in the previous step:

$$\widehat{VaR}_t^i = \hat{\alpha}^i + \hat{\gamma}^i M_t \quad (9)$$

where $\hat{\alpha}^i$ and $\hat{\gamma}^i$ and the coefficient estimate obtained from Equation (8).

We then move to the third step where the system returns is estimated using the following equations:

$$R_t^{system} = \alpha_t^{system|i} + \beta_t^{system|i} R_t^i + \gamma_t^{system|i} M_t^{system} + \varepsilon_t^{system|i} \qquad (10)$$

Where R_t^{system} is the return of stock market indices for the system of interest, $\alpha_t^{system|i}$ is the constant, β gives the contribution of the return R_t^i for each financial sector to the real economy, M_t^{system} is the vector of contemporaneous control variables, $\varepsilon_t^{system|i}$ is the error term. The 1 percent quantiles of returns for the system are again obtained from the quantile regression.

In the fourth step, the predicted $CoVaR$ of the system will be computed. Just as it has been explained previously, the predicted $CoVaR$ is the VaR of the system conditional on a situation of distress within the financial sector represented by the computed quantile regression obtained in the previous steps. Therefore, the estimated CoVaR requires the use of the computed $\widehat{VaR}_t^i(1\ percent)$ obtained in Equation (9), given all the significant control variables in Equation (10):

$$Co\widehat{VaR}_t^{system|i} = \hat{\alpha}_t^{system|i} + \hat{\beta}_t^{system|i} VaR_t^i + \hat{\gamma}_t^{system|i} M_t^{system} \qquad (11)$$

Where $\hat{\alpha}_t^{system|i}, \hat{\beta}_t^{system|i}\ and\ \hat{\gamma}_t^{system|i}$ and derived from Equation (10)

The fifth step of the estimation process involves the estimation of $\widehat{CoVaR}_t^i$ which, as explained above, is the difference between the $CoVaR$ at the 1 percent quantile and the $CoVaR$ at the 50 percent quantile. The $CoVaR$ at the 50 percent quantile is calculated just as it is done for the 1 percent quantile with the only difference being that the returns of the 50 percent is taken at each step. The estimated $CoVaR$ at the 50 percent is considered as a median state conditioning event. Therefore, the $\widehat{CoVaR}$ is the marginal contribution of the financial sector to systemic risk:

$$\Delta\widehat{CoVaR}_t^i(q) = \widehat{CoVaR}_t^{system|i}(q) - \widehat{CoVaR}_t^{system|i}(50\%) \qquad (12)$$

Empirically, the $\widehat{CoVaRs}$ are negative because they are computed from the worst 1 percent returns to of the financial sector of interest. Within this framework, the financial sector with the largest $\Delta\widehat{CoVaR}$ in absolute terms is the sector that contributes relatively the most to systemic risk during the turbulent periods.

In the sixth and final step, this study follows Bernal et al., (2014) to test for the significance and the stochastic dominance of the $\Delta CoVaRs$ in order to rank the financial sector according to their contribution to systemic risk. The aim of the test of significance is to identify a systemically risky financial sector while that of the dominance test is to test the significance of the ranking obtained from the $\Delta CoVaRs$ in order to check whether a given financial sector i does contribute more to systemic risk than the other financial sector j. This study adopts the Bernal et al., (2014) significance test based on the two-sample bootstrap Kolmogorov-Smirnov statistics developed by Abadie (2002) and defined as follows:

$$D_{mn} = (\frac{mn}{m+n})^{\frac{1}{2}} sup_x |F_m(x) - G_n(x)| \tag{13}$$

Where $F_m(x)$ and $G_n(x)$ represent the CDFs of the $CoVaRs$ related to the 1 percent and 50 percent quantiles and $m\,and\,n$ stands for the size of each sample. The null hypothesis is the equality of the CDFs of the $CoVaRs$ related to the 1 percent and 50 percent quantiles:

$$H_0: \Delta CoVaR_t^{system|i}(q) = CoVaR_t^{system|i}(q) - CoVaR_t^{system|i}(50\%) = 0 \tag{14}$$

For the dominance test, this study also relies on the bootstrap Kolmogorov-Smirnov (KS) test developed by Abadie (2002). The two-sample KS test for dominance is defined as follows:

$$D_{mn} = (\frac{mn}{m+n})^{\frac{1}{2}} sup_x |A_m(x) - B_n(x)| \tag{15}$$

Where $A_m(x)$ and $B_n(x)$ respectively are the CDFs of the $CoVaRs$ related to the two financial sectors and $m\ and\ n$ stands for the size of each sample.

$$H_0: |\Delta CoVaR_t^{system|i}(q)| > |\Delta CoVaR_t^{system|j}(q)| \tag{16}$$

Finally, given that the estimated $\Delta CoVaRs$ are negative, the interpretation of the null hypothesis and the comparison of the results of the bootstrap KS test will rely on the absolute values of $\Delta \widehat{CoVa}R$.

7.3 DATA

This study will extract data from major banks in the countries highlighted. The portfolio credit risk of these banks has a direct and major impact on the health of their financial systems. Data include a stock market index, Treasury bill rate, interbank rate and volatility index. The study also utilised stock returns of major bank holding companies (publicly traded firms) from 2006 to 2018. Publicly traded firms are companies listed on each country's stock exchange. For example, in South Africa, we have ABSA, Standard Bank, FirstRand Bank group (FNB), Nedbank and Capitec. In Nigeria, we have five (5) banks that control 60 percent of the overall assets in the market and they include Guarantee Trust Bank (GTB), Zenith Bank, First Bank, United Bank for

Africa (UBA) and Access Bank. In Kenya, we have five (5) out of forty-one (41) banks that controls 49.9 percent of the total market shares. They include Kenya Commercial banks (KCB), Equity bank, Cooperative bank, Standard Chartered Bank, and Barclays bank. In the case of Egypt, we have five (5) out of forty (40) banks, which acquired a combined share of 59.6 percent out of the total market assets. They include the National Bank of Egypt, Bank Misr, Commercial International Bank, Qatar National Bank, Banque du Caire. It must be noted that no distinction is made either the bank has an international affiliation or not. Other variables include volatility index, Liquidity spread, yield spread change, banking index and stock market index. The study period, which is 28 years has witnessed several cycles and is long enough to examine how correlations have changed over time. Data sources included Bloomberg and www.investing.com (Company level data as well as equity index), IMF~International Financial Statistics (Treasury bill and interbank rate) and FRED (Volatility index). The volatility of the stock price index is the 360-day standard deviation of the return on the national stock market index

7.4 ESTIMATION RESULT AND DISCUSSIONS

The result of the estimation for the CoVaR for the measure of systemic risk is presented in this section and it is divided into 4 subsections based on the different economies estimated for. The estimation for Egypt is given in subsection 1 while those of Kenya, Nigeria and South Africa are given in subsections 2, 3 and 4 respectively.

7.4.1 Egypt

The quantile result for the Egyptian economy is presented in this section. Table 7.1 and 7.2 reports quantile regressions results for the 1 and 50 percents quantile returns, for the Egyptian banking sector, respectively. Table 7.3 and 7.4 provides the 1 and 50 percents quantile estimation result for the Egyptian system's equity return which is used to proxy the real economy. The pseudo-R^2 which measures the goodness-of-fit of the quantile regression is also reported in each of the tables. It must be noted that the pseudo-R^2 has a similar interpretation as the standard R^2. The estimated pseudo-R^2 obtained values imply that our estimated models have the appropriate specification. The estimation of the models is conducted using the bootstrapped quantile regressions developed by Buchinsky (1995). This estimation method has the advantage that does not assume that the estimated standard errors are i.i.d. which may not be true when we consider financial data (Koenker, 2005).

7.4.1.1 Banking Index Quantile Regression

The banking sector quantile regression was estimated with the banking sector returns (ebindex) as the dependent variable while volatility index (evix), stock market index (easi), liquidity spread (els), and yield spread change (eysc) were the independent variables.

Table 7. 1: Quantile regressions for Egypt (Banking Index @1 percent)

Dependent Variable: EBINDEX				
Method: Quantile Regression (tau = 0.01)				
Sample: 7/01/2008 12/26/2017				
Included observations: 496				
Ordinary (IID) Standard Errors & Covariance				
Sparsity method: Kernel (Epanechnikov) using residuals				
Bandwidth method: Hall-Sheather, bw=0.0088703				
Estimation successfully identifies unique optimal solution				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-12.4659	1.163456	-10.7146	0.0000
EASI	1.628778	0.135448	12.02512	0.0000
EVIX	-0.0613	0.006577	-9.31977	0.0000
EYS	-0.03657	0.025264	-1.44745	0.1484
EYSCHANGE	0.086358	0.047619	1.813507	0.0704
Pseudo R-squared	0.235413	Mean dependent var		-0.07404
Adjusted R-squared	0.229184	S.D. dependent var		1.009677
S.E. of regression	1.455351	Objective		6.625831
Quantile dependent var	-1.79557	Restr. objective		8.66589
Sparsity	6.734457	Quasi-LR statistic		61.19767

Prob(Quasi-LR stat)	0.0000			

Source: Estimation

With respect to the Egyptian bank index at 1 percent, the study observed that only yield spread change not statistically significantly affect the Egyptian banking index at the 1 percent level of significance and it is negative (See Table 7.1). Equity return and yield spread change positively and significantly affect the banking index, while volatility index negatively affects banking index.

The results for the Egyptian bank index show that liquidity spread, credit spread change, and volatility index all have a negative impact on the 50 percent (normal state) quantile returns of the banking index whereas market equity return has a negative impact (Table 7.2).

Table 7. 2: Quantile regressions for Egypt (Banking Index 50 percent)

Dependent Variable: EBINDEX				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-15.6756	1.014731	-15.448	0.0000
EVIX	-0.0782	0.006497	-12.0369	0.0000
EYS	-0.09605	0.023678	-4.05655	0.0001
EYSCHANGE	-0.20122	0.07666	-2.62488	0.0089
EASI	2.255457	0.110529	20.40608	0.0000
Pseudo R-squared	0.481907	Mean dependent var		-0.07404
Adjusted R-squared	0.477686	S.D. dependent var		1.009677
S.E. of regression	0.619083	Objective		116.9614
Quantile dependent var	-0.0393	Restr. objective		225.7537
Sparsity	1.231032	Quasi-LR statistic		706.9992
Prob(Quasi-LR stat)	0			

Source: Estimation

7.4.1.2 System Quantile regression

Having estimated the banking sector quantile regression using the Egyptian banking sector returns as the dependent variable, the quantile regression for the whole economy is therefore estimated using the stock market index as a proxy for the whole economy. The banking sector returns (ebindex), volatility index (evix), liquidity spread (els), yield spread change (eysc) and each individual returns now become the independent variables. The results are presented as follows.

Table 7. 3: Quantile regressions for Egypt (System 1 percent)

Dependent Variable: EASI						
Variable	System	SystemADIBE	SystemSAUDE	SystemCOMIE	SystemQNBAE	SystemNBE
C	6.979771*** (0.1286)	7.050604*** (0.07035)	7.377876*** (0.125822)	5.499205*** (0.079472)	5.541676*** (0.158118)	6.25219*** (0.10251)
EBINDEX	0.242349*** (0.022185)	0.2837*** (0.01004)	0.247739*** (0.017136)	0.070221*** (0.007032)	0.163511*** (0.012171)	0.310892*** (0.012307)
EVIX	0.020366*** (0.003266)	0.024248*** (0.00175)	0.013313*** (0.002117)	0.019188*** (0.001385)	0.031668*** (0.002235)	0.0073*** (0.001853)
ELS	0.032664*** (0.011602)	0.036921*** (0.00603)	0.035581*** (0.006053)	0.009178*** (0.003637)	0.075635*** (0.005802)	0.014276** (0.006124)
ESYC	-0.01165 (0.01449)	-0.01753* (0.01047)	-0.01286 (0.012158)	-0.01087 (0.007313)	0.033184*** (0.011458)	-0.00501 (0.011482)
ADIBE		-0.07946*** (0.0265)				
SAUDE			-0.09939** (0.044434)			
COMIE				0.445868*** (0.0146)		
QNBAE					0.399674*** (0.037244)	
NBE						0.369239*** (0.028815)

Source: Estimation

Note that standard error is in parenthesis, while *** means significant at 1 percent level of significance, ** means significant at 5 percent level of significance, * means significant at 10 percent level of significance,

With respect to the 1 percent quantile regression for the Egyptian equity return, the result as presented in Table 7.4 show that liquidity spread, volatility index and Egyptian banking index all positively and significantly affect equity return while that of the yield spread change is not statistically significant. Furthermore, the major banks are also found to significantly impact on the real economy. The result indicates that SAUDE and AIDBE negatively impact on the system during the crisis period.

Table 7.4: Quantile regressions for Egypt (System 50 percent)

Dependent Variable: EASI						
Variable	System	SystemADIBE	SystemSAUDE	SystemCOMIE	SystemQNBAE	SystemNBE
C	7.996425*** (0.074367)	7.230397*** (0.086846)	8.587903*** (0.183497)	5.982514*** (0.128595)	6.09553*** (0.219381)	7.053597*** (0.163075)
EBINDEX	0.171616*** (0.014)	0.148778*** (0.01239)	0.225686*** (0.02499)	0.0509*** (0.011378)	0.058744*** (0.016887)	0.252861*** (0.019578)
EVIX	-0.00128 (0.002334)	-0.00139 (0.002159)	-0.00706** (0.003087)	0.017924*** (0.002241)	0.014546*** (0.003102)	-0.00119 (0.002947)
ELS	0.070903*** (0.010062)	0.01597** (0.007567)	0.061974*** (0.008827)	0.063069*** (0.005884)	0.086451*** (0.008049)	0.052097*** (0.009742)
EYSC	0.0586*** (0.014202)	0.0586*** (0.012922)	0.050111*** (0.017732)	0.054338*** (0.011833)	0.063384*** (0.015898)	0.066599*** (0.018265)
ADIBE		0.309917*** (0.03272)				
SAUDE			-0.21355*** (0.064802)			
COMIE				0.41073*** (0.023625)		
QNBAE					0.470251*** (0.051673)	
NBE						0.302472*** (0.045839)

Source: Estimation

Note that standard error is in parenthesis, while *** means significant at 1 percent level of significance, ** means significant at 5 percent level of significance, * means significant at 10 percent level of significance,

With respect to the real economy which is proxied by the equity return. The result of the 50 percent quantile regression as presented in Table 7.3 indicates that liquidity spread, yield spread change and the Egyptian banking index are statistically significant with a positive sign whereas the volatility index is not statistically significant and with a negative sign. With respect to the individual banks, all the banks contributed significantly and positively at the 1 percent level of significance except SAUDE which was negative although also significant. In summary, it can be seen that in both the normal state and distress state, SAUDE impacts on the system negatively.

7.4.1.3 Marginal Contributions of Egyptian Banks to Systemic Risk (ΔCoVaR) Results

The marginal contributions (ΔCoVaR) of each bank to the systemic risk is covered in this subsection. The ΔCoVaR is the difference between the VaR of the system when a bank is in a normal state and the VaR when it is in distress (1 percent). The interpretation of the ΔCoVaR is based on absolute value although it is negative. Furthermore, a ΔCdoVaR with a value of zero implies that none of the banks contributes to the systemic risk. However, a value different from zero would mean that such a bank contributes to systemic risk. The bank with the largest absolute value is believed to contribute the most to systemic risk during periods of distress.

Table 7. 5: Summary Statistics for the ΔCoVaR for all Banks

Variable	Mean	Std.Dev	Min	Max
ADIBE	-0.35476	0.127791	-0.71683	-0.04776
SAUDE	-0.37964	0.086908	-0.68591	-0.19726
COMIE	-0.22853	0.083607	-0.38704	-0.03411
QNBAE	-0.29527	0.087376	-0.54021	-0.04089
NBE	-0.30907	0.06483	-0.59579	-0.10339

Source: Estimation

Based on the result presented in Table 7.5, the absolute ΔCoVaR value of SAUDE is the largest. These findings suggest that SAUDE contributes more to systemic risk relatively to other banks. This confirms the result of the system quantile regression of which it indicates that SAUDE impacts negatively on the system both in the normal state as well as during distress periods. The second systemically more important bank is ADIBE, followed by NBE, QNBAE and COMIE in that order. As indicated in the quantile result, ADIBE impacts negatively on the system during the distress period.

Table 7. 6: Significance Test for Egyptian Banks

Method	Value	Probability
AIDB	0.086816	0.001
SAUD	0.10437	0.0000
COMI	0.080618	0.0029
QNBA	0.046851	0.2209
NBE	0.074073	0.0081

Source: Estimation

The result as presented in Table 7.6 reports the results of the significance test for Egyptian banks. The Kolmogorov-Smirnov (KS) statistics and the corresponding p-value indicate that under the null hypothesis that the CoVaR estimate during the crisis period (1 percent quantile) and the CoVaR estimate in normal time (50 percent quantile) are equal. The estimation implies that the null hypothesis for all the Egyptian banks except QNBA was rejected. This implies that each of the banks has a significant systemic impact on the real economy during the period of crisis.

7.4.2 Kenya

The quantile result for the Kenyan economy is presented in this section. Table 7.7 and 7.8 reports quantile regression results for the 1 percent and 50 percent quantile returns for the Egyptian banks respectively. Table 7.9 and 7.10 provides the quantile estimation result for the Egyptian system's equity return which is used to proxy the real economy. The pseudo-R^2 which measures the goodness-of-fit of the quantile regression is also reported in each of the tables. It must be noted that the pseudo-R^2 has a similar interpretation as the standard R^2.

7.4.2.1 Banking Index Quantile Regression VaR

The banking sector quantile regression was estimated with the banking sector returns (kbindex) as the dependent variable while volatility index (kvix), stock market index (kasi), liquidity spread (kls), and yield spread change (kysc) were the independent variables.

Table 7. 7: Quantile regressions for Kenya (Banking Index @1 percent)

Dependent Variable: KBINDEX				
Method: Quantile Regression (tau = 0.01)				
Sample: 7/01/2008 12/26/2017				
Included observations: 496				
Ordinary (IID) Standard Errors & Covariance				
Sparsity method: Kernel (Epanechnikov) using residuals				
Bandwidth method: Hall-Sheather, bw=0.0088703				
Estimation successfully identifies unique optimal solution				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.82727	0.129287	-21.8681	0.0000
KVIX	-0.02345	0.004585	-5.11306	0.0000
KLS	0.012629	0.005968	2.115947	0.0349
KYSC	-0.05277	0.009127	-5.7822	0.0000
KASI	0.857711	0.036195	23.6969	0.0000
Pseudo R-squared	0.324888	Mean dependent var		-0.09364
Adjusted R-squared	0.319388	S.D. dependent var		1.0018
S.E. of regression	1.137637	Objective		4.52096
Quantile dependent var	-1.41838	Restr. objective		6.696609
Sparsity	3.102217	Quasi-LR statistic		141.681
Prob(Quasi-LR stat)	0.0000			

Source: Estimation

Table 7. 8: Quantile regressions for Kenya (Banking Index @50 percent)

Dependent Variable: KBINDEX				
Method: Quantile Regression (Median)				
Sample: 7/01/2008 12/26/2017				
Included observations: 496				
Ordinary (IID) Standard Errors & Covariance				
Sparsity method: Kernel (Epanechnikov) using residuals				
Bandwidth method: Hall-Sheather, bw=0.12274				
Estimation successfully identifies unique optimal solution				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.22143	0.270801	-15.5887	0.0000
KVIX	-0.00636	0.009604	-0.66199	0.5083
KLS	0.044827	0.012501	3.585793	0.0004
KYSC	0.097724	0.019116	5.112112	0.0000
KASI	1.691237	0.075813	22.30804	0.0000
Pseudo R-squared	0.514718	Mean dependent var		-0.09364
Adjusted R-squared	0.510764	S.D. dependent var		1.0018
S.E. of regression	0.531255	Objective		103.2849
Quantile dependent var	-0.457	Restr. objective		212.8346
Sparsity	1.293044	Quasi-LR statistic		677.7784
Prob(Quasi-LR stat)	0.0000			

Source: Estimation

Estimated result for Kenyan banks presented in Tables 7.7 indicates that liquidity spread, volatility index and equity return all have a positive impact on the 1 percent quantile returns of the banking index whereas credit spread change has a negative and significant impact. With regards the Kenya bank index at 50 percent (normal state), the result indicates that liquidity spread, credit spread change and equity return still have a positive and significant impact on the banking index while volatility has a negative impact, although not significant (See Table 7.8).

7.4.2.2 System Quantile regression

The next step is to estimate the quantile regression for the whole economy using the stock market index as a proxy for the whole economy. The banking sector returns, the volatility index (kvix), liquidity spread (kls), yield spread change (kysc) and each individual returns now becomes the independent variables. The results are presented as follows.

Table 7. 9: Quantile regressions for Kenya (System 1 percent)

Dependent Variable: KASI						
Variable	System	SystemBBK	SystemCOOPK	SystemEQTBK	SystemKENCB	SystemSTDCBK
C	2.014499*** (0.0302)	1.228322*** (0.076234)	0.355454 (0.334418)	1.754043*** (0.115184)	-4.07158*** (0.250542)	-2.70469*** (0.30469)
KBINDEX	0.011251*** (0.00241)	0.39874*** (0.006742)	0.374626*** (0.010462)	0.395737*** (0.009975)	0.135652*** (0.011348)	0.342634*** (0.006952)
KVIX	-0.00168 (0.003064)	-0.00164 (0.002246)	0.018466*** (0.003228)	0.009027*** (0.002652)	0.001772 (0.00127)	0.026004*** (0.001689)
KLS	-0.02058*** (0.00482)	-0.00036 (0.002348)	-0.00196 (0.003161)	-0.00297 (0.003295)	0.000694 (0.001597)	0.010883*** (0.001947)
KYSC	0.403189*** (0.008619)	0.343703*** (0.003694)	-0.02187*** (0.004921)	-0.02101*** (0.005179)	-0.00756** (0.002546)	-0.0189*** (0.003075)
BBK		0.126591*** (0.011681)				
COOPK			0.215257*** (0.042209)			
EQTBK				0.035736*** (0.014489)		
KENCBK					0.780199*** (0.030498)	
STDCBK						0.455978*** (0.029444)

Source: Estimation

Note that standard error is in parenthesis, while *** means significant at 1 percent level of significance, ** means significant at 5 percent level of significance, * means significant at 10 percent level of significance,

Examining the NSE all-share index 1 percent quantile returns, the result indicates that the Kenyan banking index significantly and positive impact, while that of volatility and credit spread change has a negative and significant impact. The individual banks are also found to affect the economy significantly. However, liquidity spread was not significant (See Table 7.9). Turning to the 50 percent quantile result for the Kenyan economy, the result as presented in Table 7.10 indicate that the banking index, liquidity spread, credit yield spread and volatility index all enter significantly with a negative sign.

Table 7. 10: Quantile regressions for Kenya (System 50 percent)

Dependent Variable: KASI						
Variable	System	SystemBBK	SystemCOOPK	SystemEQTBK	SystemKENCB	SystemSTDCBK
C	2.675034 (0.0457)	4.457257*** (0.135715)	2.684365*** (0.498345)	1.384124*** (0.129108)	-2.42798*** (0.762256)	6.890133 (0.798445)
KBINDEX	0.343703 (0.003646)	0.265829*** (0.012003)	0.343787*** (0.01559)	0.29895*** (0.011181)	0.12542*** (0.034526)	0.382952 (0.018219)
KVIX	-0.01814 (0.00463)	-0.01736*** (0.003998)	-0.01824*** (0.00481)	-0.01697*** (0.002973)	-0.00896** (0.003863)	-0.03957 (0.004425)
KLS	-0.02685*** (0.007279)	-0.05216*** (0.004179)	-0.02698*** (0.00471)	-0.02528*** (0.003693)	-0.01863*** (0.004859)	-0.04352 (0.005103)
KYSC	0.03437*** (0.013038)	0.403189*** (0.006575)	-0.03084*** (0.007332)	-0.02868*** (0.005806)	-0.0174** (0.007747)	-0.04474 (0.008057)
BBK		-0.2307*** (0.020796)				
COOPK			-0.00111 (0.062899)			
EQTBK				0.159257*** (0.01624)		
KENCBK					0.618525*** (0.092789)	
STDCBK						-0.39167 (0.077157)

Source: Estimation

Note that standard error is in parenthesis, while *** means significant at 1 percent level of significance, ** means significant at 5 percent level of significance, * means significant at 10 percent level of significance,

The Kenyan banking sector contributes positively and significantly to the real economy, hence, there is a need for continued surveillance because a default in the banking sector may lead to a major collapse in the real economy. In the case of the individual major banks, the result shows that all the major banks except standard chartered bank of Kenya contribute positively and significantly to the economy during normal times except BBK which impacts negatively and significantly to the system.

7.4.2.3 Marginal Contributions of Kenyan Banks to Systemic Risk (ΔCoVaR) Results

The marginal contributions (ΔCoVaR) of each bank to the systemic risk is covered in this subsection. The ΔCoVaR is the difference between the VaR of the system when a bank is in a normal state and the VaR when it is in distress (1 percent). The interpretation of the ΔCoVaR is based on the discussion in subsection 7.4.1.3.

Table 7. 11: Summary Statistics for the ΔCoVaR for all Kenyan Banks

Variable	Mean	Std.Dev	Min	Max
BBK	-0.3785	0.261878	-1.02813	0.015233
COOPK	-0.32193	0.096889	-0.57411	-0.12061
EQTBK	-0.33314	0.105198	-0.55912	-0.07418
KENCBK	-0.23037	0.071656	-0.47643	-0.04455
STDCBK	-0.33575	0.217205	-0.92667	0.117926

Source: Estimation

Table 7.11 reveals that BBK is on average the most systemically important bank in Kenya with an average ΔCoVaR of -0.37. In a more explicit term, it implies that a 0.37 basis point is being added to the VaR when BBK is in a distressed state. This is followed by STDCBK, EQTBK, COOPK and KENCBk with a ΔCoVaR of -0.33575, -0.33314, -0.32193 and 0.23037 respectively.

Table 7. 12: Significance Test for Kenyan Banks

	Value	Probability
BBK	0.182572	0.0000
COOP	0.172595	0.0000
EQTBK	0.136712	0.0000
KENCB	0.144609	0.0000
STDCBK	0.203858	0.0000

Source: Estimation

Table 7.12 reports the results of the significance test for banks in five major banks in Kenya. It indicates the KS statistics and the corresponding p-value with the null hypothesis that the CoVaR estimate in crisis or extreme period (1 percent quantile) and the CoVaR estimate in normal time (50 percent quantile) are equal. The results show that the null hypothesis for all the banks could be rejected at the 1% significance level. This finding presupposes that each of the banks has a significant impact on the real economy during a period of turmoil. Therefore, one can conclude that the banks contribute significantly to systemic risk in Kenya.

7.4.3 Nigeria

The quantile result for the Nigerian economic system is presented in this section. Table 7.13 and 7.14 reports quantile regressions results for the 1 and 50 percents quantile returns, for the Egyptian banks, respectively. Table 7.15 and 7.16 provides the quantile estimation result for the Egyptian system's equity return which is used to proxy the real economy. The pseudo-R^2 which measures the goodness-of-fit of the quantile regression is also reported in each of the tables. It must be noted that the pseudo-R^2 has a similar interpretation as the standard R^2.

7.4.3.1 Banking Index Quantile Regression VaR

The Nigerian banking sector quantile regression was estimated with the banking sector returns (nbindex) as the dependent variable while volatility index (nvix), stock market index (nasi), liquidity spread (nls), and yield spread change (nysc) were the independent variables.

Table 7. 13: Quantile regressions for Nigeria (Banking Index @1 percent)

Dependent Variable: NBINDEX				
Method: Quantile Regression (tau = 0.01)				
Sample: 7/01/2008 12/26/2017				
Included observations: 496				
Ordinary (IID) Standard Errors & Covariance				
Sparsity method: Kernel (Epanechnikov) using residuals				
Bandwidth method: Hall-Sheather, bw=0.0088703				
Estimation successfully identifies unique optimal solution				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-12.7922	0.564671	-22.6542	0.0000
NVIX	-0.01164	0.002391	-4.86731	0.0000
NLS	-0.00016	0.001592	-0.10316	0.9179
NYSC	-0.00417	0.005606	-0.74391	0.4573
NASI	1.167013	0.054168	21.54429	0.0000
Pseudo R-squared	0.191347	Mean dependent var		0.041688
Adjusted R-squared	0.184759	S.D. dependent var		1.142128
S.E. of regression	1.59839	Objective		5.449029
Quantile dependent var	-1.255	Restr. Objective		6.738404
Sparsity	2.651613	Quasi-LR statistic		98.23448
Prob(Quasi-LR stat)	0.0000			

Source: Estimation

Table 7. 14: Quantile regressions for Nigeria (Banking Index @50 percent)

Dependent Variable: NBINDEX				
Method: Quantile Regression (Median)				
Sample: 7/01/2008 12/26/2017				
Included observations: 496				
Ordinary (IID) Standard Errors & Covariance				
Sparsity method: Kernel (Epanechnikov) using residuals				
Bandwidth method: Hall-Sheather, bw=0.12274				
Estimation successfully identifies unique optimal solution				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-14.4879	1.396002	-10.3782	0.0000
NVIX	0.11433	0.005911	19.34294	0.0000
NLS	-0.00336	0.003937	-0.85382	0.3936
NYSC	-0.03271	0.01386	-2.35966	0.0187
NASI	1.220549	0.133916	9.114255	0.0000
Pseudo R-squared	0.251272	Mean dependent var		0.041688
Adjusted R-squared	0.245172	S.D. dependent var		1.142128
S.E. of regression	0.943619	Objective		147.7856
Quantile dependent var	-0.11597	Restr. Objective		197.3822
Sparsity	1.304512	Quasi-LR statistic		304.1541
Prob(Quasi-LR stat)	0.0000			

Source: Estimation

The results for the Nigerian banking index at the 1 percent quantiles as presented in Tables 7.14 show that volatility and equity return significant impact on the banking index, although the volatility enters negatively while equity returns enter positively. With respect to the normal state or 50 percent quantile, the result indicates that volatility and credit spread change has a negative and significant impact on the banking sector while equity returns enter positively and significantly (See Table 7.14).

7.4.3.2 System Quantile regression

Having estimated the banking sector quantile regression using the Nigerian banking sector returns as the dependent variable, the next step is to estimate the quantile regression for the whole economy which is proxied by the stock market index. The banking sector returns (nbindex), volatility index (nvix), liquidity spread (nls), yield spread change (nysc) and each individual returns now become the independent variables. The results are presented in Tables 7.15 and 7.16.

Table 7. 15: Quantile regressions for Nigeria (System 1 percent)

Variable	System	SystemACBN	SystemGTBN	SystemUBAN	SystemZENITHBN	SystemFBN
C	9.946935*** (0.025182)	9.557796*** (0.18838)	7.434249*** (0.115093)	9.743152*** (0.134693)	9.867929*** (0.209832)	10.13006*** (0.040181)
NBINDEX	-0.00312** (0.001363)	-0.00818 (0.007807)	-0.04061*** (0.004595)	-0.01233 (0.009816)	-0.00243 (0.007117)	0.001298 (0.005951)
NVIX	0.007346*** (0.00078)	-0.00456*** (0.001646)	0.005882*** (0.001101)	-0.00672*** (0.001399)	-0.00315** (0.001528)	0.000652 (0.001227)
NLS	0.005614** (0.0027)	0.0075*** (0.000824)	-0.00427*** (0.000615)	0.007184*** (0.000806)	0.007543*** (0.000792)	0.003707*** (0.00068)
NYSC	5.58E-05 (0.006023)	5.58E-05 (0.002897)	-0.01605*** (0.002108)	0.003618 (0.002818)	0.005099* (0.002769)	0.007089*** (0.002324)
ACBN		0.062959** (0.025963)				
GTBN			0.321839*** (0.014053)			
UBAN				0.042049** (0.020969)		
ZENITHBN					0.010826 (0.026306)	
FBN						-0.09898*** (0.011282)

Source: Estimation

Note that standard error is in parenthesis, while *** means significant at 1 percent level of significance, ** means significant at 5 percent level of significance, * means significant at 10 percent level of significance,

The result for the Nigerian economy at the 1 percent quantile as presented in Table 7.15 indicate that the real economy is influenced negatively by the stock volatility, while liquidity spread and credit spread change impacts on the economy positively. Furthermore, the result indicates that all the banks except Zenith have a significant impact on the real economy during the crisis period.

Table 7. 16: Quantile regressions for Nigeria (System 50 percent)

Dependent Variable: NASI						
Variable	System	SystemACBN	SystemGTBN	SystemUBAN	SystemZENITHBN	SystemFBN
C	10.70609*** (0.0457)	12.24416*** (0.328973)	7.53102*** (0.250074)	11.65708*** (0.276039)	5.880962*** (0.361009)	10.96481*** (0.0966)
NBINDEX	-0.02506*** (0.003646)	0.139417*** (0.013634)	0.070634*** (0.009983)	0.14863*** (0.020116)	0.029143** (0.012244)	0.149216*** (0.014312)
NVIX	0.002814*** (0.0046)	-0.03437*** (0.0028)	-0.0066*** (0.002392)	-0.02458*** (0.002867)	-0.00058 (0.002628)	-0.02703*** (0.002952)
NLS	-0.00701*** (0.00729)	0.001846 (0.00144)	-0.00066 (0.001336)	0.002224 (0.001652)	-3.83E-05 (0.001363)	0.001793 (0.001636)
NYSC	0.343703*** (0.013038)	0.090669 (0.005059)	-0.0077* (0.004579)	-0.00641 (0.005775)	-0.00769 (0.004764)	-0.00984* (0.005589)
ACBN		-0.20562*** (0.04534)				
GTBN			0.369701*** (0.039534)			
UBAN				-0.14535*** (0.042973)		
ZENITHBN					0.590711*** (0.045259)	
FBN						-0.109*** (0.027132)

Source: Estimation

Note that standard error is in parenthesis, while *** means significant at 1 percent level of significance, ** means significant at 5 percent level of significance, * means significant at 10 percent level of significance,

In the case of the Nigerian economy at the 50 (normal) percent quantile returns, both volatility and banking index still have a statistically significant impact, although volatility enters negatively, while banking index is positive (See Table 7.16). This means that policymakers should keep an eye on the banking system and ensure that it is stable as, during this period, it tends to contribute significantly to the growth of the economy. The same goes for all the banks as the result indicates that they contribute significantly to the economy.

7.4.3.3 Marginal Contributions of Nigerian Banks to Systemic Risk (ΔCoVaR) Results

The marginal contributions (ΔCoVaR) of each Nigerian bank to the systemic risk are covered in this subsection. The ΔCoVaR is the difference between the VaR of the system when a bank is in a normal state and the VaR when it is in distress (1 percent). The interpretation of the ΔCoVaR is based on the discussion in subsection 7.4.1.3.

Table 7. 17: Summary Statistics for the ΔCoVaR for all Banks

Variable	Mean	Std.Dev	Min	Max
ACBN	-0.35121	0.140693	-0.93264	0.004845
GTBN	-0.24954	0.112444	-0.76456	-0.05514
UBAN	-0.35776	0.130013	-0.90498	-0.03411
ZENITHBN	-0.35873	0.182079	-1.03887	0.055229
FBN	-0.30268	0.159254	-0.97406	-0.00872

Source: Estimation

The result as presented in Table 7.17 reveals that Zenith bank is on the average more systematically important bank in Nigeria. It, therefore, means that Zenith bank contributes more to systemic risk in the system during crisis periods. This is followed by UBA with the second largest absolute ΔCoVaR estimate. The GTB contributes the least to systemic risk with a ΔCoVaR absolute value.

Table 7. 18: Significance Test for Nigerian Banks

Method	Value	Probability
ACBN	0.100593	0.0001
GTBN	0.083537	0.0018
UBAN	0.093601	0.0003
ZENITHN	0.087123	0.001
FBN	0.119637	0.000

Source: Estimation

The result as presented in Table 7.17 reports the results of the significance test for the Nigerian banking sector. It shows the KS statistics and the corresponding p-value under the null hypothesis that the CoVaR estimate during the crisis period (1 percent quantile) and the CoVaR estimate in normal time (50 percent quantile) are equal. The results show that the null hypothesis for all the banks was rejected. This implies that each of the banks has a significant systemic impact on the real economy during the period of crisis.

7.4.4 South Africa

The quantile result for the South African economy is presented in this section. Table 7.19 and 7.20 reports quantile regressions results of the 1 and 50 percents quantile returns, for the South African economy, respectively. Table 7.21 and 7.22 provides the quantile estimation result for the Egyptian system's equity return which is used to proxy the real economy. The pseudo-R^2 which measures the goodness-of-fit of the quantile regression is also reported in each of the tables. It must be noted that the pseudo-R^2 has a similar interpretation as the standard R^2.

7.4.4.1 Banking Index Quantile Regression VaR

The South African banking sector quantile regression was estimated with the banking sector returns (sbindex) as the dependent variable while volatility index (svix), stock market index (sasi), liquidity spread (sls), and yield spread change (sysc) were the independent variables.

Table 7. 19: Quantile regressions for South Africa (Banking Index @1 percent)

Dependent Variable: SBINDEX				
Method: Quantile Regression (tau = 0.01)				
Sample: 7/01/2008 12/26/2017				
Included observations: 496				
Ordinary (IID) Standard Errors & Covariance				
Sparsity method: Kernel (Epanechnikov) using residuals				
Bandwidth method: Hall-Sheather, bw=0.0088703				
Estimation successfully identifies unique optimal solution				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-22.496	0.320188	-70.2586	0.0000
SVIX	0.034291	0.001597	21.47076	0.0000
SLS	-0.24993	0.020193	-12.3773	0.0000
SYSC	-0.14946	0.017542	-8.5198	0.0000
SASI	2.020053	0.028302	71.37376	0.0000
Pseudo R-squared	0.453655	Mean dependent var		-0.06414
Adjusted R-squared	0.449204	S.D. dependent var		0.976597
S.E. of regression	0.776516	Objective		2.661153
Quantile dependent var	-1.04616	Restr. objective		4.87083
Sparsity	1.242439	Quasi-LR statistic		359.2929
Prob(Quasi-LR stat)	0.0000			

Source: Estimation

Results for the South African banking index show that volatility and equity returns have a positive impact on the 1 percent quantile returns of the banking index whereas liquidity spread and credit spread change have a negative impact (See Table 7.19).

Table 7. 20: Quantile regressions for Kenya (Banking Index @50 percent)

Dependent Variable: SBINDEX				
Method: Quantile Regression (Median)				
Sample: 7/01/2008 12/26/2017				
Included observations: 496				
Ordinary (IID) Standard Errors & Covariance				
Sparsity method: Kernel (Epanechnikov) using residuals				
Bandwidth method: Hall-Sheather, bw=0.12274				
Estimation successfully identifies unique optimal solution				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-44.7396	1.146354	-39.0277	0.0000
SVIX	0.098906	0.005718	17.29732	0.0000
SLS	-0.55741	0.072294	-7.71028	0.0000
SYSC	-0.40804	0.062806	-6.49682	0.0000
SASI	4.067098	0.10133	40.13713	0.0000
Pseudo R-squared	0.618426	Mean dependent var		-0.06414
Adjusted R-squared	0.615317	S.D. dependent var		0.976597
S.E. of regression	0.389448	Objective		74.65123
Quantile dependent var	-0.49199	Restr. objective		195.6402
Sparsity	0.88519	Quasi-LR statistic		1093.451
Prob(Quasi-LR stat)	0.0000			

Source: Estimation

With respect to the South African bank index at 50 percent (normal state), the result is similar to that of the 1 percent quantile as it indicates that volatility and equity returns have a positive impact on the 50 percent quantile returns of the banking index whereas liquidity spread and credit spread change have a negative impact (See Table 7.20).

7.4.4.2 System Quantile regression

Having estimated the banking sector quantile regression using the South African banking sector returns as the dependent variable, the quantile regression for the whole economy is therefore estimated using the stock market index as a proxy for the real economy. The banking sector returns (sbindex), volatility index (svix), liquidity spread (sls), yield spread change (sysc) and each individual returns now become the independent variables. The results are presented as follows.

Table 7. 21: Quantile regressions for South Africa (System 1 percent)

Dependent Variable: SASI						
Variable	System	SystemABSA	SystemCAPSA	SystemFNBSA	SystemNEDBSA	SystemSTDBSA
C	11.01584*** (0.012619)	17.03887*** (0.936711)	13.1648*** (0.287626)	5.750581*** (0.128529)	6.000636*** (0.3004132)	8.945576*** (0.5007153)
SBINDEX	-0.03353*** (0.003844)	0.186294*** (0.011342)	0.304096*** (0.016693)	-0.14962*** (0.0086014)	0.125543*** (0.0012357)	0.182657*** (0.0092165)
SVIX	0.111633*** (0.000707)	-0.02409*** (0.001148)	-0.04742*** (0.0020818)	-0.02318*** (0.0003817)	-0.02188*** (0.0012357)	-0.02662*** (0.004454)
SLS	0.049472*** (0.01243)	-0.005650 (0.019796)	0.048209*** (0.018723)	-0.02159*** (0.0053404)	0.155895*** (0.0119415)	0.074518*** (0.0210995)
SYSC	0.049472*** (0.010712)	-0.015051 (0.017033)	0.013338 (0.01569)	-0.039804*** (0.0044696)	0.053882*** (0.003247)	0.026241** (0.0181481)
ABSA		-0.54649*** (0.13555)				
CAPSA			-0.18815*** (0.02519)			
FNBSA				0.66791*** (0.016133)		
NEDBSA					0.492416*** (0.0288446)	
STDBSA						0.207558*** (0.0516818)

Source: Estimation

Note that standard error is in parenthesis, while *** means significant at 1 percent level of significance, ** means significant at 5 percent level of significance, * means significant at 10 percent level of significance,

The result for the South African economy provides an interesting argument for regulators. At the 1 percent quantile, the result indicates that the banking sector, credit yield spread and liquidity spread contributes positively and significantly to the real economy, while volatility negatively impacts on the real economy. In addition to that, the result as presented in Table 7.21 indicates the banks also have a significant impact on the real economy although only ABSA and CASA were negative

Table 7. 22: Quantile regressions for South Africa (System 50 percent)

Dependent Variable: SASI						
Variable	System	SystemABSA	SystemCAPSA	SystemFNBSA	SystemNEDBSA	SystemSTDBSA
C	11.00883*** (0.0154)	18.5197*** (1.213975)	12.48171*** (0.274959)	5.474303*** (0.357594)	6.676295*** (0.3524022)	7.253394*** (0.3569853)
JBINDEX	-0.02576*** (0.004691)	0.153418*** (0.008954)	0.279337*** (0.015958)	-0.17145*** (0.0239307)	0.146033*** (0.0061886)	0.144654*** (0.0065709)
SVIX	0.13217*** (0.000863)	-0.02821*** (0.000906)	-0.03598*** (0.00199)	-0.01876*** (0.001062)	-0.01413*** (0.0014496)	-0.02309*** (0.001031)
SLS	0.108191*** (0.015177)	0.13672*** (0.015628)	0.103502*** (0.017899)	0.017094 (0.014858)	0.098555*** (0.014008)	0.150191*** (0.015043)
SYSC	0.202366*** (0.0130)	0.110961*** (0.013447)	0.090118*** (0.0150016)	0.02378** (0.012435)	0.069583*** (0.012112)	0.116193*** (0.01294)
ABSA		-0.65935*** (0.107011)				
CAPSA			-0.12752*** (0.0240809)			
FNBSA				0.705189*** (0.044886)		
NEDBSA					0.424288*** (0.0338364)	
STDBSA						0.395449*** (0.036847)

Source: Estimation

Note that standard error is in parenthesis, while *** means significant at 1 percent level of significance, ** means significant at 5 percent level of significance, * means significant at 10 percent level of significance,

For the 50 percent quantile returns, the result is similar to that of the 1 percent quantile as liquidity spread, credit yield change and bank index returns have a positive effect. Volatility, on the other hand, has a negative impact. All the banks also have a significant impact on the real economy although only ABSA and Capitec were negative (See Table 7.20).

7.4.4.3 Marginal Contributions of South African Banks to Systemic Risk (ΔCoVaR) Results

Table 7. 23: Summary Statistics for the ΔCoVaR for all Banks

Variable	Mean	Std.Dev	Min	Max
ABSA	-0.14842	0.051288	-0.3664	0.006128
CAPSA	-0.14117	0.050131	-0.38313	-0.07375
FNBSA	-0.09585	0.035566	-0.28283	-0.05818
NEDBSA	-0.14364	0.052123	-0.31103	-0.05783
STDBSA	-0.14679	0.041867	-0.3519	-0.05462

Source: Estimation

Based on the result presented in Table 7.23, the absolute ΔCoVaR value of ABSA is the largest. These findings suggest that ABSA contributes more to systemic risk relatively to other banks. This confirms the result of the system quantile regression of which it indicates that ABSA impacts negatively on the system both in the normal state as well as during distress periods. The second systemically more important bank is Standard bank, followed by NEDBSA, CAPSA and FNBSA in that order. As indicated in the quantile result, CAPSA impacts negatively on the system during the distress period. The findings of the study are contrary to that of Manguzvane and Mwamba (2017), who concluded that FNB is the most systemically important bank, although, on the point that STDBSA is the second most relatively systemically important bank, this result confirms the result of their study. However, it must be noted that some of the proxies for the variables used were different as well as the data frequency and time frame. For example, they used the banking index as a proxy for the system dependent variable while this study used the stock market index. This might have accounted for the differences in result.

Table 7. 24: Significance Test for South African Banks

Method	Value	Probability
ABSA	0.091736	0.0004
CAPSA	0.105784	0.0000
FNBSA	0.075198	0.0069
NEDBSA	0.051086	0.1458
STDBSA	0.049057	0.1788

Source: Estimation

The result as presented in Table 7.23 reports the results of the significance test for South African banks. It shows the Kolmogorov-Smirnov (KS) statistics and the corresponding p-value under the null hypothesis that the CoVaR estimate during the crisis period (1 percent quantile) and the CoVaR estimate in normal time (50 percent quantile) are equal. The results show that the null hypothesis for all the banks except Nedbank and Standard bank was rejected. This implies that each of the banks has a significant systemic impact on the real economy during the period of crisis.

7.5 CHAPTER SUMMARY

This chapter employed the $CoVaR$ model developed by Adrian and Brunnermeier (2011) to measure systemic risk. The $CoVaR$ model is believed to be very useful in capturing risk spillover as well as capturing systemic risk through the VaR of an institution conditional on other institutions in distress. The systemic risk contribution of the banking and financial sector for a sample period of July 2006 to December 2017 using weekly macroeconomic and financial data was estimated. The risk contribution of the financial sector on the banking sector was equally estimated for emerging African economies.

The result based on the 1 percent and 50 percent quantiles indicates that the banking sector contributes positively and significantly to the real economy for all the countries at both the normal state (50 percent quantile) and extreme event (1 percent quantile) except for Nigeria at the extreme event or 1 percent quantile. Furthermore, the result indicates that stick market volatility is a major source of systemic risk not only to the banking sector but as well to the real economy. The result indicates that at both the normal state and extreme event, stock market volatility can be seen as a source of systemic risk to the real economy except for Kenya during a normal state. This result is similar to the findings of Drakos and Kouretas (2015) in the case of the US and UK. It must be noted that during periods of the financial crisis, extreme events which is usually preceded by risk build-up tend to spill across financial institutions which contributes to systemic risk.

In addition, the result further revealed that equity return is a key determinant causing systemic risk episode for both the 1 percent and 50 percent quantile regression for all the countries in this study. This study, therefore, concludes that the banking sector, stock market volatility contributes greatly to systemic risk in emerging African economies. The individual bank also contributes significantly to systemic risk for all the economies although the magnitudes are relatively different. Nigerian banks tend to contribute relatively more to systemic risk followed by Kenyan banks, Egyptian banks and then South Africa. This finding is of great interest to policymakers since it shows that the banking sectors as well as stock market volatility have a negative impact on the real economy. This result is plausible as the banking and financial sector for most emerging economies constitute a greater proportion of the real economy. There is therefore need for a regulatory framework to reduce risk emanating from the banking sector as well as the financial markets.

CHAPTER EIGHT

SUMMARY, CONCLUSIONS AND POLICY RECOMMENDATIONS

This chapter focuses on the summary, conclusions and policy recommendation of the study. The chapter is divided into four sections. Section 1 given a summary of the study and this include the background of the study as well as the objectives. The discussion of main findings is presented in Section 2 while the policy recommendation is presented in Section 3. The limitations of the study and areas for further research are presented in Section 4.

8.1 SUMMARY OF THE STUDY

The main objective of this study is to measure systemic risk in African emerging economies and develop a macroprudential regulatory framework to mitigate or limit the effect of such risk. The extent of the loss caused by the 2007/08 global financial crisis (GFC) has forced policymakers all over the world to respond promptly in order to mitigate its effect, a process in which they are still engaged in, particularly in advanced economies. The nature of the GFC has also reinforced the obligation of the regulatory authorities to improve their surveillance and strengthening of the financial stability framework. When the GFC started, the general perception was that there will only be a limited impact on African economies due to their limited financial depth and low integration of their financial system with other world economies especially the United States and European capital market. This perception later changed due to increasing trade linkages and disruption of trade finance that accompanied the GFC.

Furthermore, the rise in capital flows into the continent from the advanced countries has increased the vulnerability of the financial system thereby posing risks to macroeconomic and financial stability. Although the surge in the capital flow has the potential of propelling growth, on one hand, it also serves as a source of systemic risk. Essentially, financial sector misalignment due to excessive risk exposure is a major constraint to economic growth. This will lead to a reduction in income, increased income inequality, increased unemployment level, loss of confidence in the system and social unrest. This has indeed revealed Africa’s vulnerability to external shocks as well as their low resilience level.

However, while conventional monetary policy is believed to inhibit capital flows from intensifying overheating pressures and resultant inflation, it is not sufficient to guard against the risk of financial instability. Policy makers are now faced with the challenge of not only understanding and determining the reforms needed for the financial system, but also the regulatory structures and policy instruments needed to enhance financial stability. According, there has been an increasing effort by monetary authorities and other stakeholders in the financial sector for the adoption of policies that will aid better management of systemic risk. However, before such policies can be adopted, it is essential to understand systemic risk and how it can be measured and monitored. Therefore, this study contributed to the body of knowledge by measuring systemic risk in emerging African economies. To the best of my knowledge, there have not been any studies that have been conducted for the measure of systemic risk with the context of emerging African economies.

More specifically, the study intends to

1. Developing financial stress index (FSI) for the Emerging African economy
2. Investigate the possibility of Early Warning Signal (EWS) helping in predicting and preventing or minimising the effects of the crisis on financial institutions.
3. Assess the resilience of individual banking companies to adverse macroeconomic and financial market conditions using stress testing technique.
4. Identify the source of fluctuation within the system.
5. Identify and measure systemic risk emanating from the capital flow (surge) as well as its effects on financial stability.

The target economies include South Africa, Egypt, Nigeria, and Kenya. These target economies are drawn from the list of the countries with the largest economies as well as stock market development. The study used various macroeconomic and financial data such as real GDP, inflation; stock market returns etc. and they were sourced from the Countries' central banks databases, Bankscope and Bloomberg database. The study covered a period between 1980 and 2017, although subject to the availability of data from the various sources.

8.2. DISCUSSION OF MAIN FINDINGS AND CONCLUSION

8.2.1 Main Findings and Conclusions of the Construction of Financial Stress Index (FSI)

The first objective of the study is to construct a financial stress index (FSI) for emerging African economies. The FSI which is aimed at revealing the functionality of the financial system a single aggregate indicator that is constructed to reflect the systemic nature of financial instability and as well to measure the vulnerability of the financial system to both internal and external shocks.

The FSI provides aggregate information from various markets segments as a measure of financial stress in the financial system as a whole and these market segments include the money market, bond market, foreign exchange market. This is very useful in monitoring the financial system as well as being used as a dependent variable in an early signal warning model as in the case of the second objective in this study. Furthermore, the FSI is also useful in gauging the effectiveness of government measures to mitigate financial stress, as well as for macroprudential policymaking.

There are basically four steps in the construction of FSI and they include 1) selection of market and market-specific indicators, 2) data gathering and transformation, 3) construction of the index, and lastly is to test the forecasting accuracy of the FSI. Four market segments comprising of thirteen indicators were selected and the data were transformed using empirical normalization. This normalises the indicator into the same scale of between zero and one (0, 1). With regards to the estimation techniques, basically, there are a number of estimating techniques including the variance equal weight (VEW) method, the principal component analysis, portfolio aggregation theory, regression method among others. For this study, the VEW and PCA methods were used. The forecasting accuracy of the model was tested using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Theils Inequality Coefficient (TIC), Thiel U^2 Coefficient, and Symmetric MAPE among others.

The result indicates that extreme values of FSIs are associated with well-known financial stress cases. It must be noted that the FSI constructed based on PCA gives importance to indicators with higher volatility. The result shows that both the domestic and international shocks created uncertainty in the economies under consideration. On the international scene, we have a financial crisis while on the domestic scene; we have slow growth, banking crisis, energy crisis, labour crisis, coupled with political uncertainty. The FSI is also useful and appropriate as the dependent variable in an early signal warning model, and as well be used to gauge the effectiveness of government measures to mitigate financial stress.

The models forecasting performance was tested using the ordinary least square methods. The forecast estimate includes real gross domestic product (rgdp) and consumer price index (CPI) as explanatory variables while the FSI_N is the dependent variable and based on the model diagnostics, it was revealed that the models were well fitted and stable. For South Africa, the FSI (FSI_S_KD) developed in the study was compared with the FCI (FSI_S_KM) developed by Kabundi and Mbelu (2017). The result indicates performs better than the FCI_S_KM developed by Kabundi and Mbelu (2017). This is because the RMSE (0.8835), MAE (0.6765), Theil's U coefficient (0.5900), U^2 (3.3148) and SMAPE (114.9979) of the FSI_S_KD model were lower than that of FCI_S_KM (See Table 3.4). In the case of Nigeria (FSI_N_KD), since there was no previously known FSI constructed, the model forecasting accuracy was tested based on the result of the OLS regression. The result for the FSI_N_KD model affirms that the model is reliable and the FSI_N can be used for prediction of a future crisis.

8.2.2 Main Findings and Conclusions of the Development of an Early Warning Signal (EWS) Model

The aim of the objective is to develop an early warning signal (EWS) model to predict the possibility of the occurrence of a financial crisis in emerging African countries. Relevant literature was reviewed and the general consensus was that there are two basic approaches to developing an EWS model and they are the static or signal extraction approach as well as the dynamic or non-sample specific approach. The signal approach is aimed at identifying and monitoring certain variables that tend to behave in an unusual manner in the build-up to financial or economic distress, while the dynamic choice of the threshold or non-sample-specific approach focuses more on the volatility of the indicators. An alternative model was proposed by Frankel and Rose (1996), that is, the logit or probit regression models to estimate the probability of an approaching currency crisis. The logit model was based on the binary dependent variable where the crisis variable assumes the value of one for the period of crisis and zero for the non-crisis period.

However, due to the issue of having a post-crisis bias as discussed earlier, a multinomial logit model was introduced by Bussiere and Fratzscher (2006). The identification and prediction of the state of the financial system are very important for the design of appropriate policy such as countercyclical capital buffers which can help reduce large losses associated with the financial crisis. In order to predict systemic risk in the financial system an early warning signal (EWS) the multinomial logit model built by Bussiere and Fratzscher (2006) was adopted to afford policy makers ample time to prevent or mitigate potential financial crisis The estimated model predicted the probability of a crisis (which takes the value of 1 for the first year, 2 for the other crisis years and 0 for non-crisis years), as a function of a vector of potential explanatory variables. While previous studies have focused on advanced economies and low-income countries, this study contributed to the existing literature by developing an EWS model the context of emerging African economies.

In summary, the result suggests that emerging African economies are more likely to face financial crisis as debts continue to rise without a corresponding capacity to withstand capital flow reversal as well as excessive FX risk due to currency exposure. The result further indicates that rising debt exposure increases the probability or likelihood of the economies remaining in a state of crisis. This result confirms the significance of financial stability framework that fits Africa’s emerging economies characteristics such as rising debt profile liquidity and currency risk exposure. According to Caggiano et al. (2014), exposure to currency risk is a source of threat to the soundness of the financial system. The model goodness-of-fit and predictive power which was tested based on the value of the pseudo-R^2 statistics is 0.55; this means that the independent variables can well predict the dependent variable.

8.2.3 Main Findings and Conclusions of Stress Testing the Resilience of the Financial Sector to macroeconomic Shocks for Emerging African Economies

The third objective is to test the resilience of the financial sector using stress testing technique. Macro stress testing is a multi-step simulation process aimed at estimating the impact of credit risk shock on macroeconomic as well as financial sectors. It is a popular risk management tool for evaluating the effect of an extreme event on the financial sector and it provides information on the nature of the system under exceptional but plausible shocks or the impact of a range of future shocks to certain macroeconomic variables of the system. Furthermore, it is useful in terms of quantifying losses that emanate from market breakdown during a crisis. Several approached has been used for stress testing and they include the value at risk (VaR), expected shortfall (ES), regression, vector autoregression (VAR), vector error correction model (VECM), global vector autoregression (GVAR) among others. In this study, a two-step approach was employed in this chapter. The first step involves analyzing the determinants of credit risk in 4 Emerging African economies during the period 2006m1 to 2012m12 using the panel Auto Regressive Distribution Lag (ARDL) model. Second, the vector autoregressive (VAR) models were employed to assess the resilience of the financial system as well as the economy to adverse credit risk shocks.

The panel ARDL was used to determine the drivers on credit risk using the PMG estimation technique. The PMG estimation technique was selected instead of the MG based on the Hausman test and it is believed to be more efficient. The macroeconomic drivers of credit risk were assessed using a panel ARDL model. The estimation was divided into two namely: the macro model and financial model. From the estimation, it was evident that all the variables under both the macro and financial model jointly determine credit risk, although when examined on an individual basis only, UMP, IBR, and INF have a significant impact on NPL in the long run. Although EXR does not significantly affect NPL in the long run, it was, however, significant in the short run.

Turning to the macro stress testing, the VAR methodology was employed to stress test the emerging African economy financial sector and the result indicated that there a significant relationship between changes in output gap (GAP) and the nonperforming loans. This is similar to the study conducted by the Bank of Japan (2009), Bank of Ghana (2006) and Bank of England (2005) Vazquez et al. (2012), as well as Jordan and Tucker (2013). The result further revealed that for the accumulated responses over a two year (24 months) period, an innovation or positive shock to output gap equal to one standard deviation, ceteris paribus, resulted in a persistent reduction in nonperforming loans for South Africa and Nigeria. It is believed that growth in output tends to increase employment thereby reducing nonperforming loans. Significant relationships were also established between inflation and nonperforming loans. In all, South Africa and Nigeria's financial system seems more resilient to credit losses associated with this scenario without threatening financial stability compared to Kenya and Egypt.

8.2.4 Main Findings and Conclusions on the Sources of Capital Flow Surge into Emerging African Economies

This objective examined the sources of capital flows surge and their impact on macroeconomic variables. Since after the GFC, there has been a surge in capital flows to emerging markets. A major reason for these flows has been as a result of the unconventional policies implement by most developed economies. These policies led to a high level of global liquidity and a low interest rate in these countries. Capital flows has the tendency of generating overheating, excessive credit creation and asset price bubbles, loss of competitiveness due to currency appreciation, and increased vulnerability to crisis. These phenomena have thus raised concerns over potential external imbalances, as well as risk to macroeconomic and financial stability.

This study employed a $P{-}SVAR$ to investigate the source capital flow surge within the system. The approach was chosen due to its flexibility and efficiency in combining past, present and future events and also because it allows for recovery of interesting pattern, especially in financial related studies. The PSVAR was estimated using eight endogenous variables, namely; RGDP, INFR, INTR, CRGT, EXPR, UMP, EXHR, BMSP and one exogenous variable, namely, FDI as proxy for monetary and capital flow shock. Monthly data from 2006m1 to 2017m12 was used. The main findings of the result indicate that capital flow, which is proxied by FDI, is influenced by a wide variety of macroeconomic variables. Furthermore, the result of the estimation indicates that inflation seems to have more impact on FDI than exchange rate; thus maintaining inflation stability could ensure economic stability and in turn, stimulate FDI. FDI is a key element of capital financing for an emerging economy. It is a strong form of capital flow and carries spillover benefits that are conducive to growth. FDI responds positively to growth in real gross domestic product. For the exchange rate, it was clear that high fluctuation in the exchange rate has a great influence on the movement of capital flows into the emerging African economies. This is because the result revealed that a shock or innovation to the exchange rate leads to a deterioration in capital flows.

This result is similar to the findings of Agénor et al., (2014) who opined that exchange rate depreciation can be linked to declining external funding conditions during the crisis period. Currency depreciation can aggravate the currency mismatches of domestic borrowers with large foreign-currency debt exposures which may undermine their creditworthiness. This according to Agenor et al. (2014) has great implication for financial stability in a number of ways. To start with, high fluctuations in currency can disrupt exchange rate expectation, which, in turn, tend to lead to changes in capital flows. Also, the level of exchange rate can propagate the level of shock within the system due to the fact that it influences the value placed by the foreign lender on domestic assets. This will further lead to a deterioration of the exchange rate. Furthermore, other major drivers of FDI to emerging African economies include export growth and unemployment. There is, therefore, need for the implementation of capital controls framework tame massive capital inflows. Nevertheless, such a mechanism should not undermine the impact of capital inflows on employment, growth and financial stability.

8.2.5 Main Findings and Conclusions on Measuring Systemic Risk in Emerging African Economies

The fifth objective of the study is aimed at identifying and measuring the sources of systematic risk and its impact on the stability of the financial system. Identifying the risk spillover and as well capturing the systemic risk of an institution conditioned upon another being in distress in very important for central banks authorities and policymakers. Systemic risk measure captures the likelihood for the spreading of financial distress across banks or financial institutions by gauging this increase in tail co-movement. During the financial crisis, losses tend to spread quickly through the financial system thereby threatening the functioning of the financial system and by extension the real economy.

Although, banks play a very important role in the proper functioning of an economy since they provide the necessary liquidity to the markets and help to promote economic growth, however, a distressed bank or banking sector can be systemic as it may serve as a potential source of financial crisis and instability to the system. A brief history of systemic risk measurement was given right from the period when the CDS and PCA were used to measure systemic risk up to the point where the CoVaR approach developed by Adrian and Brunnermeier (2011) was used. This study adopts the CoVaR model developed by Adrian and Brunnermeier (2011) to measure systemic risk. The CoVaR model is useful in studying risk spillovers as well as capturing systemic risk through the VaR of an institution conditional on other institutions in distress. CoVaR as defined by Adrian and Brunnermeier (2011) as the $CoVaR_q^{j|i}$ as the VaR_q^j of institution j condition on some event $C(R^i)$ of institution i.

The main finding of the study indicates that at the normal and extreme event the banking sector contributes positively and significantly to the real economy for all the countries except for Nigeria at the extreme event or 1 percent quantile. Furthermore, the result indicates that stock market volatility is a major source of systemic risk not only to the banking sector but as well to the real economy. That is, at both the normal state and extreme event, stock market volatility can be seen as a source of systemic risk to the real economy except for Kenya during a normal state. Furthermore, the result revealed that equity return is a key determinant causing systemic risk episode for both the 1 percent and 50 percent quantile regression for all the countries in this study. This study, therefore, concludes that the banking sector, stock market volatility contributes greatly to systemic risk in emerging African economies. The individual bank also contributes significantly to systemic risk for all the economies although the magnitudes are relatively different. Nigerian banks tend to contribute relatively more to systemic risk followed by Kenyan banks, Egyptian banks and then South Africa. This finding is of great interest to policy makers since it shows that the banking sectors as well as stock market volatility have a negative impact on the real economy. This result is plausible as the banking and financial sector for most emerging economies constitute a greater proportion of the real economy. There is therefor need for a regulatory framework to reduce risk emanating from the banking sector as well the financial markets.

8.3 POLICY RECOMMENDATION

It is clear from the study that African countries to financial crisis due high debts profile and currency exposure as well as capital flow surge due to monetary policies being implemented by some of the advanced countries and as well major trading partners. There is, therefore, a need for a macroprudential policy that will fit African economies as well as the implementation of capital controls framework tame massive capital inflows. Efforts should be made to reduce the rising debts profile of most countries and that will require a greater level of commitment from their respective government and central banks. However, these should be in the interest of the growth and stability of the financial system and the real economy at large. In the case of the banking sector, since it has a great impact on triggering systemic risk, more effort should be utilized to continue to monitor its performance so that potential risk can be detected early and nip in the bud.

8.4 LIMITATIONS OF THE STUDY AND AREAS FOR FURTHER RESEARCH

A major limitation in this study was data. There is a paucity of high-frequency financial data for most African countries apart from South Africa. This makes it difficult to make a comparison between the period before the crisis and after the crisis. Furthermore, some other important variables were dropped or not used because data were not available for all the countries and in some instances, the researcher had to reduce the study period to accommodate more variables. In measuring systemic risk, area for further research should include measuring the impact of other financial institutions such as the insurance sector, other financial services and non-banking financial institution on systemic risk.

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APPENDIXES

Appendix A: CORRELATION ANALYSIS

Appendix A-1-Egypt

Table A- 1: Correlation Analysis for Egypt

```
. correlate ervi eils eicb ervb esbs ervu ervg erve ecmu ecmg ecme erva ecma em
> m ebm efm eem FSI_E
(obs=144)
```

	ervi	eils	eicb	ervb	esbs	ervu	ervg
ervi	1.0000						
eils	0.1673	1.0000					
eicb	0.3089	0.8223	1.0000				
ervb	0.0075	0.0807	0.0978	1.0000			
esbs	0.0304	0.7640	0.6968	0.0225	1.0000		
ervu	0.3212	0.1167	0.1925	0.0085	0.1192	1.0000	
ervg	0.2874	0.1189	0.1871	0.0063	0.1110	0.8746	1.0000
erve	0.2669	0.0560	0.1383	−0.0175	0.0899	0.9150	0.8385
ecmu	−0.0235	−0.3669	−0.2775	−0.0211	−0.5393	0.0278	0.0514
ecmg	0.0056	−0.4677	−0.3658	−0.0425	−0.5877	0.0095	0.0483
ecme	0.0165	−0.3613	−0.2492	−0.0405	−0.4525	0.0038	0.0294
erva	−0.0826	−0.0645	−0.0917	−0.0177	0.0170	−0.0154	0.0524
ecma	0.1060	−0.1916	−0.1014	0.0244	−0.1670	−0.1634	−0.1430
emm	0.1673	1.0000	0.8223	0.0807	0.7640	0.1167	0.1189
ebm	0.0304	0.7640	0.6968	0.0225	1.0000	0.1192	0.1110
efm	−0.0235	−0.3669	−0.2775	−0.0211	−0.5393	0.0278	0.0514
eem	0.1060	−0.1916	−0.1014	0.0244	−0.1670	−0.1634	−0.1430
FSI_E	0.1060	−0.1916	−0.1014	0.0244	−0.1670	−0.1634	−0.1430

	erve	ecmu	ecmg	ecme	erva	ecma	emm
erve	1.0000						
ecmu	0.0944	1.0000					
ecmg	0.0776	0.9677	1.0000				
ecme	0.0930	0.9503	0.9572	1.0000			
erva	0.0603	0.0892	0.0769	0.1022	1.0000		
ecma	−0.1653	0.2665	0.3365	0.4595	0.0280	1.0000	
emm	0.0560	−0.3669	−0.4677	−0.3613	−0.0645	−0.1916	1.0000
ebm	0.0899	−0.5393	−0.5877	−0.4525	0.0170	−0.1670	0.7640
efm	0.0944	1.0000	0.9677	0.9503	0.0892	0.2665	−0.3669
eem	−0.1653	0.2665	0.3365	0.4595	0.0280	1.0000	−0.1916
FSI_E	−0.1653	0.2665	0.3365	0.4595	0.0280	1.0000	−0.1916

	ebm	efm	eem	FSI_E
ebm	1.0000			
efm	−0.5393	1.0000		
eem	−0.1670	0.2665	1.0000	
FSI_E	−0.1670	0.2665	1.0000	1.0000

.

Source: Estimation

Appendix A-2-Kenya

Table A- 2: Correlation Analysis for Kenya

```
. correlate krvi kils kicb krvb ksbs krvu krvg krve kcmu kcmg kcme krva kcma km
> m kbm kfm kem FSI_K
(obs=144)
```

	krvi	kils	kicb	krvb	ksbs	krvu	krvg
krvi	1.0000						
kils	0.2204	1.0000					
kicb	0.2866	0.7191	1.0000				
krvb	0.1208	−0.0627	0.0000	1.0000			
ksbs	0.0786	−0.0000	0.2057	0.1657	1.0000		
krvu	−0.0418	−0.2408	−0.2411	0.1320	−0.0424	1.0000	
krvg	−0.0272	−0.0933	−0.1669	0.0486	−0.1559	0.4688	1.0000
krve	0.1123	−0.1695	−0.2409	0.0214	−0.1295	0.3817	0.4928
kcmu	0.0064	0.3689	0.3829	0.0753	0.2445	0.0195	0.0216
kcmg	0.0484	0.2220	0.2311	0.0772	0.5034	0.0905	0.0303
kcme	0.2285	0.1844	0.4361	0.0524	0.5752	0.0139	0.0684
krva	−0.0139	0.0175	0.0036	−0.0157	0.1843	−0.0266	0.0285
kcma	−0.1194	−0.1218	−0.0428	−0.1574	0.0327	−0.0640	0.0787
kmm	0.2204	1.0000	0.7191	−0.0627	−0.0000	−0.2408	−0.0933
kbm	0.0786	−0.0000	0.2057	0.1657	1.0000	−0.0424	−0.1559
kfm	0.1123	−0.1695	−0.2409	0.0214	−0.1295	0.3817	0.4928
kem	−0.0139	0.0175	0.0036	−0.0157	0.1843	−0.0266	0.0285
FSI_K_PCA	0.1123	−0.1695	−0.2409	0.0214	−0.1295	0.3817	0.4928

	krve	kcmu	kcmg	kcme	krva	kcma	kmm
krve	1.0000						
kcmu	−0.0214	1.0000					
kcmg	−0.0312	0.2923	1.0000				
kcme	0.1161	0.3722	0.4679	1.0000			
krva	0.0349	0.2368	−0.0369	0.0752	1.0000		
kcma	0.0109	−0.0721	−0.0203	0.0440	−0.0030	1.0000	
kmm	−0.1695	0.3689	0.2220	0.1844	0.0175	−0.1218	1.0000
kbm	−0.1295	0.2445	0.5034	0.5752	0.1843	0.0327	−0.0000
kfm	1.0000	−0.0214	−0.0312	0.1161	0.0349	0.0109	−0.1695
kem	0.0349	0.2368	−0.0369	0.0752	1.0000	−0.0030	0.0175
FSI_K_PCA	1.0000	−0.0214	−0.0312	0.1161	0.0349	0.0109	−0.1695

	kbm	kfm	kem	FSI_K_~A
kbm	1.0000			
kfm	−0.1295	1.0000		
kem	0.1843	0.0349	1.0000	
FSI_K_PCA	−0.1295	1.0000	0.0349	1.0000

.

Appendix A-3-Nigeria

Table A- 3: Correlation Analysis for Nigeria

```
. correlate nils nicb nrvb nsbs nrvu nrvg nrve ncmu ncmg ncme nrva ncma nmm nbm
>   nfm nem fsi_n
(obs=144)
```

	nils	nicb	nrvb	nsbs	nrvu	nrvg	nrve
nils	1.0000						
nicb	0.9293	1.0000					
nrvb	-0.0911	-0.0759	1.0000				
nsbs	-0.0987	-0.0419	0.6382	1.0000			
nrvu	0.0443	0.0553	-0.0642	-0.0961	1.0000		
nrvg	-0.0079	0.0209	0.0124	-0.0794	0.7577	1.0000	
nrve	0.0654	0.0712	0.0024	-0.1511	0.7651	0.8339	1.0000
ncmu	-0.1903	-0.0873	-0.0356	-0.0581	-0.0262	0.0828	0.0590
ncmg	-0.1790	-0.0608	0.0206	0.0217	-0.0988	0.0793	0.0436
ncme	-0.1920	-0.1033	-0.0217	-0.0271	-0.0522	0.1055	0.0790
nrva	-0.0258	0.0281	-0.0439	-0.0225	-0.0326	0.1380	0.1231
ncma	0.0636	0.0288	0.0006	0.0310	0.0019	-0.0476	-0.0009
nmm	0.4186	0.4371	-0.0394	-0.0247	-0.0645	-0.0216	0.0093
nbm	-0.0987	-0.0419	0.6382	1.0000	-0.0961	-0.0794	-0.1511
nfm	0.0654	0.0712	0.0024	-0.1511	0.7651	0.8339	1.0000
nem	-0.0258	0.0281	-0.0439	-0.0225	-0.0326	0.1380	0.1231
fsi_n	0.0654	0.0712	0.0024	-0.1511	0.7651	0.8339	1.0000

	ncmu	ncmg	ncme	nrva	ncma	nmm	nbm
ncmu	1.0000						
ncmg	0.8422	1.0000					
ncme	0.8299	0.8143	1.0000				
nrva	0.1570	0.2193	0.1092	1.0000			
ncma	-0.2078	-0.1447	0.0788	-0.0948	1.0000		
nmm	0.0074	0.0123	0.0097	0.0845	0.0110	1.0000	
nbm	-0.0581	0.0217	-0.0271	-0.0225	0.0310	-0.0247	1.0000
nfm	0.0590	0.0436	0.0790	0.1231	-0.0009	0.0093	-0.1511
nem	0.1570	0.2193	0.1092	1.0000	-0.0948	0.0845	-0.0225
fsi_n	0.0590	0.0436	0.0790	0.1231	-0.0009	0.0093	-0.1511

	nfm	nem	fsi_n
nfm	1.0000		
nem	0.1231	1.0000	
fsi_n	1.0000	0.1231	1.0000

.

Source: Estimation

Appendix A-4-South Africa

Table A- 4: Correlation Analysis for South Africa

	srvi	sils	sicb	srvb	ssbs	srvu	srvg
srvi	1.0000						
sils	0.2095	1.0000					
sicb	0.3545	0.0814	1.0000				
srvb	0.1732	-0.0601	0.1012	1.0000			
ssbs	-0.1355	-0.4080	0.2345	0.0761	1.0000		
srvu	0.2279	0.1390	0.1066	0.1392	0.0222	1.0000	
srvg	0.1990	0.0995	0.0354	0.1879	-0.0880	0.8295	1.0000
srve	0.1716	0.0290	0.0964	0.2917	-0.0320	0.7655	0.8128
scmu	-0.2981	-0.0954	-0.0995	0.0203	0.3808	0.0205	-0.0545
scmg	-0.1044	0.2634	0.1484	0.0972	0.2077	0.0300	-0.0385
scme	-0.2725	-0.0648	0.0477	0.0662	0.5360	-0.0217	-0.1020
srva	-0.0894	-0.1608	0.0416	0.0058	-0.1170	-0.3318	-0.0780
scma	0.2895	-0.0055	0.5919	0.1142	0.2227	-0.0713	-0.0837
smm	0.3545	0.0814	1.0000	0.1012	0.2345	0.1066	0.0354
sbm	-0.1355	-0.4080	0.2345	0.0761	1.0000	0.0222	-0.0880
sfm	-0.2725	-0.0648	0.0477	0.0662	0.5360	-0.0217	-0.1020
sem	0.2895	-0.0055	0.5919	0.1142	0.2227	-0.0713	-0.0837
FSI_S	0.2895	-0.0055	0.5919	0.1142	0.2227	-0.0713	-0.0837

	srve	scmu	scmg	scme	srva	scma	smm
srve	1.0000						
scmu	-0.0108	1.0000					
scmg	0.0425	0.7072	1.0000				
scme	-0.0102	0.7045	0.7752	1.0000			
srva	-0.0112	-0.0276	-0.0713	-0.0403	1.0000		
scma	-0.0649	-0.2121	0.2546	0.1789	0.0584	1.0000	
smm	0.0964	-0.0995	0.1484	0.0477	0.0416	0.5919	1.0000
sbm	-0.0320	0.3808	0.2077	0.5360	-0.1170	0.2227	0.2345
sfm	-0.0102	0.7045	0.7752	1.0000	-0.0403	0.1789	0.0477
sem	-0.0649	-0.2121	0.2546	0.1789	0.0584	1.0000	0.5919
FSI_S	-0.0649	-0.2121	0.2546	0.1789	0.0584	1.0000	0.5919

	sbm	sfm	sem	FSI_S
sbm	1.0000			
sfm	0.5360	1.0000		
sem	0.2227	0.1789	1.0000	
FSI_S	0.2227	0.1789	1.0000	1.0000

Null Hypothesis: GDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.333672	0.4126
Test critical values:	1% level	-4.030157	
	5% level	-3.444756	
	10% level	-3.147221	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 11 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.689767	0.0000
Test critical values:	1% level	-4.029595	
	5% level	-3.444487	
	10% level	-3.147063	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on HQ, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.333672	0.4126
Test critical values:	1% level	-4.030157	
	5% level	-3.444756	
	10% level	-3.147221	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 12 (Automatic - based on HQ, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.142370	0.0071
Test critical values:	1% level	-4.030157	
	5% level	-3.444756	
	10% level	-3.147221	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: CPI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 6 (Automatic - based on HQ, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.350203	0.0628
Test critical values:	1% level	-4.028496	
	5% level	-3.443961	
	10% level	-3.146755	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(CPI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on HQ, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.386057	0.0032
Test critical values:	1% level	-4.026942	
	5% level	-3.443201	
	10% level	-3.146309	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: FSI_S_KD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on HQ, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.392042	0.3821
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

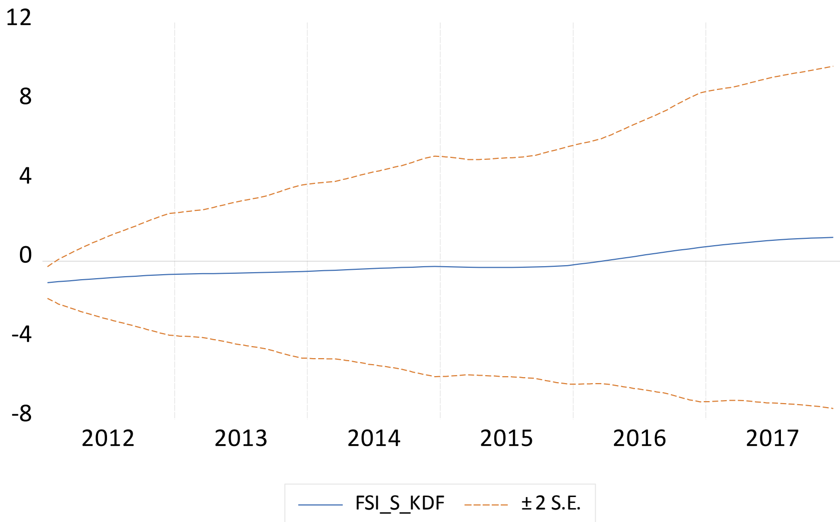
*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(FSI_S_KD) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on HQ, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.52512	0.0000
Test critical values:	1% level	-4.025924	
	5% level	-3.442712	

10% level	-3.146022

*MacKinnon (1996) one-sided p-values.



Forecast: FSI_S_KDF
Actual: FSI_S_KD
Forecast sample: 2012M01 2017M12
Included observations: 72

Root Mean Squared Error	0.883500
Mean Absolute Error	0.676503
Mean Abs. Percent Error	283.8554
Theil Inequality Coef.	0.590021
Bias Proportion	0.305327
Variance Proportion	0.095389
Covariance Proportion	0.599283
Theil U2 Coefficient	3.314881
Symmetric MAPE	114.9979

Dependent Variable: FSI_S_KD
Method: Least Squares
Date: 11/13/18 Time: 14:17
Sample (adjusted): 2006M02 2011M12
Included observations: 71 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.153986	23.04828	-0.093455	0.9258
GDPMP	0.054216	1.630437	0.033252	0.9736
INF_S	0.015449	0.040653	0.380017	0.7052
UMP_S	0.052879	0.053188	0.994193	0.3238
FSI_S_KD(-1)	0.931100	0.055481	16.78221	0.0000

R-squared	0.862110	Mean dependent var	-0.281873
Adjusted R-squared	0.853753	S.D. dependent var	1.015293
S.E. of regression	0.388270	Akaike info criterion	1.013590
Sum squared resid	9.949752	Schwarz criterion	1.172934
Log likelihood	-30.98244	Hannan-Quinn criter.	1.076956
F-statistic	103.1609	Durbin-Watson stat	1.876620
Prob(F-statistic)	0.000000		

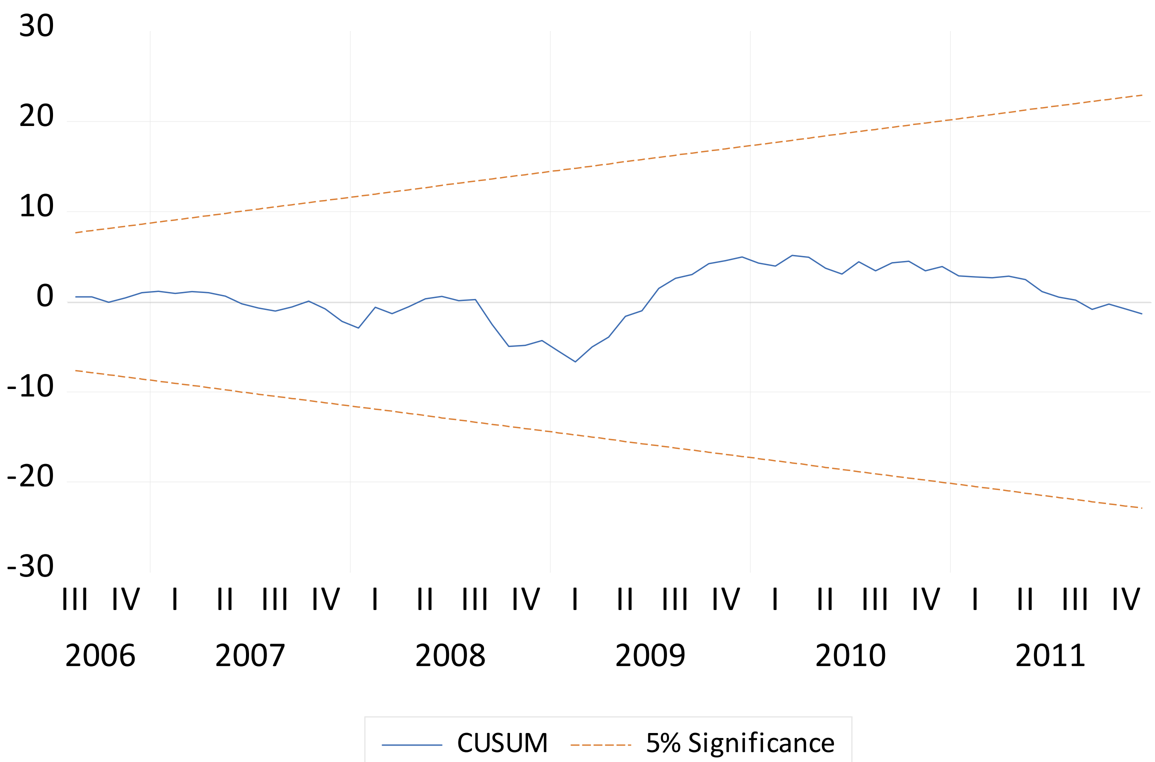
Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

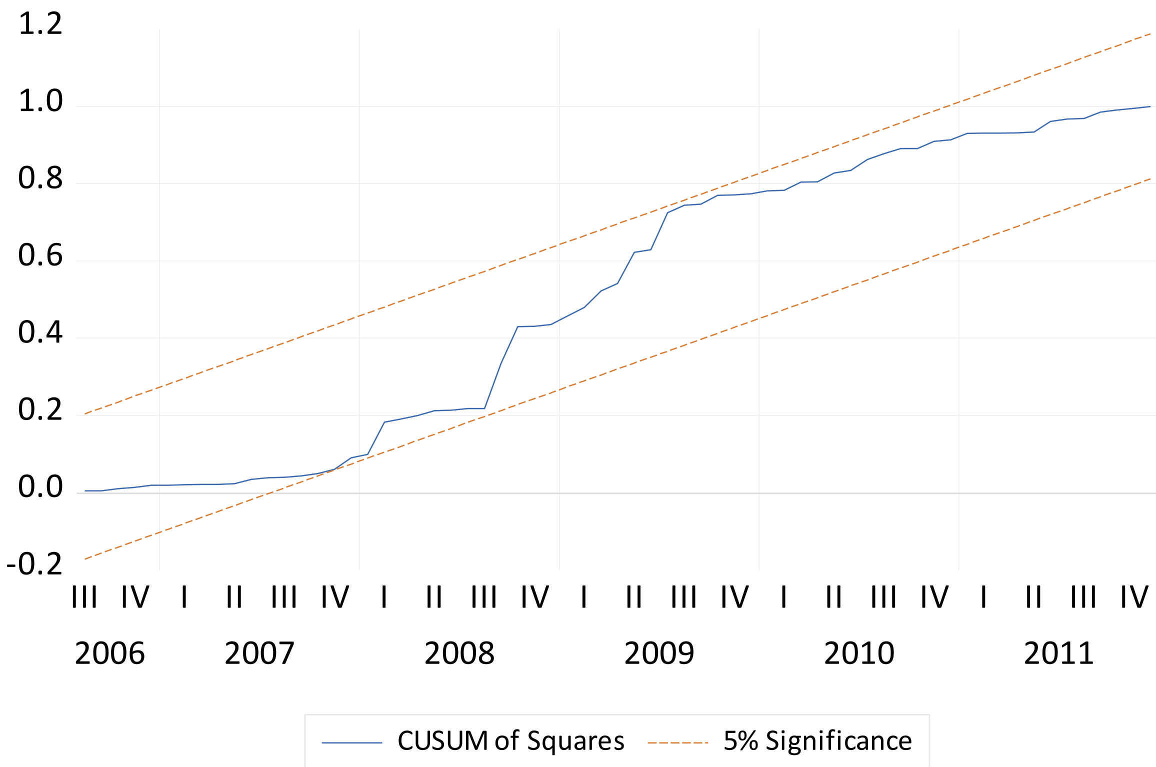
F-statistic	0.137547	Prob. F(2,64)	0.8718
Obs*R-squared	0.303877	Prob. Chi-Square(2)	0.8590

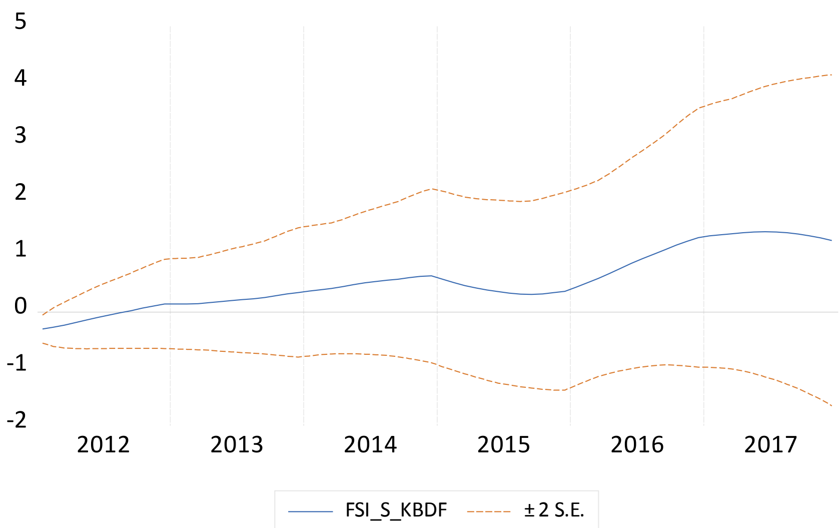
Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 11/13/18   Time: 14:18
Sample: 2006M02 2011M12
Included observations: 71
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.166513	23.71798	-0.091345	0.9275
GDPMP	0.149876	1.676699	0.089388	0.9291
INF_S	0.006418	0.043043	0.149102	0.8819
UMP_S	0.004434	0.054561	0.081269	0.9355
FSI_S_KD(-1)	-0.019767	0.068260	-0.289581	0.7731
RESID(-1)	0.066491	0.139939	0.475142	0.6363
RESID(-2)	0.040412	0.138528	0.291723	0.7714

R-squared	0.004280	Mean dependent var	-3.29E-16
Adjusted R-squared	-0.089069	S.D. dependent var	0.377014
S.E. of regression	0.393446	Akaike info criterion	1.065639
Sum squared resid	9.907167	Schwarz criterion	1.288720
Log likelihood	-30.83018	Hannan-Quinn criter.	1.154351
F-statistic	0.045849	Durbin-Watson stat	1.979716
Prob(F-statistic)	0.999575		







Forecast: FSI_S_KBDF
Actual: FSI_S_KBD
Forecast sample: 2012M01 2017M12
Included observations: 72

Root Mean Squared Error	0.965839
Mean Absolute Error	0.857914
Mean Abs. Percent Error	256.1437
Theil Inequality Coef.	0.913773
Bias Proportion	0.789002
Variance Proportion	0.136017
Covariance Proportion	0.074982
Theil U2 Coefficient	20.79085
Symmetric MAPE	183.9383

Dependent Variable: FSI_S_KBD
Method: Least Squares
Date: 11/13/18 Time: 14:16
Sample (adjusted): 2006M02 2011M12
Included observations: 71 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.649884	7.436164	-1.028741	0.3074
GDPMP	0.487961	0.531778	0.917602	0.3622
INF_S	0.042704	0.013433	3.179041	0.0023
UMP_S	0.034270	0.016012	2.140325	0.0360

FSI_S_KBD(-1)	0.901919	0.050783	17.76036	0.0000

R-squared	0.950027	Mean dependent var	0.155669
Adjusted R-squared	0.946998	S.D. dependent var	0.526627
S.E. of regression	0.121241	Akaike info criterion	-1.314260
Sum squared resid	0.970152	Schwarz criterion	-1.154917
Log likelihood	51.65624	Hannan-Quinn criter.	-1.250894
F-statistic	313.6779	Durbin-Watson stat	0.876868
Prob(F-statistic)	0.000000		

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	19.34968	Prob. F(2,64)	0.0000
Obs*R-squared	26.75435	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 11/13/18 Time: 14:16
Sample: 2006M02 2011M12
Included observations: 71
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.920963	6.170800	1.121566	0.2662
GDPMP	-0.514740	0.442415	-1.163479	0.2490
INF_S	0.020788	0.011715	1.774477	0.0807
UMP_S	-0.004838	0.012895	-0.375217	0.7087
FSI_S_KBD(-1)	-0.126410	0.049617	-2.547708	0.0133
RESID(-1)	0.600894	0.119776	5.016835	0.0000
RESID(-2)	0.139428	0.134585	1.035981	0.3041

R-squared	0.376822	Mean dependent var	-2.21E-15
Adjusted R-squared	0.318399	S.D. dependent var	0.117726
S.E. of regression	0.097193	Akaike info criterion	-1.730845
Sum squared resid	0.604578	Schwarz criterion	-1.507764
Log likelihood	68.44500	Hannan-Quinn criter.	-1.642133
F-statistic	6.449893	Durbin-Watson stat	2.034555
Prob(F-statistic)	0.000024		

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

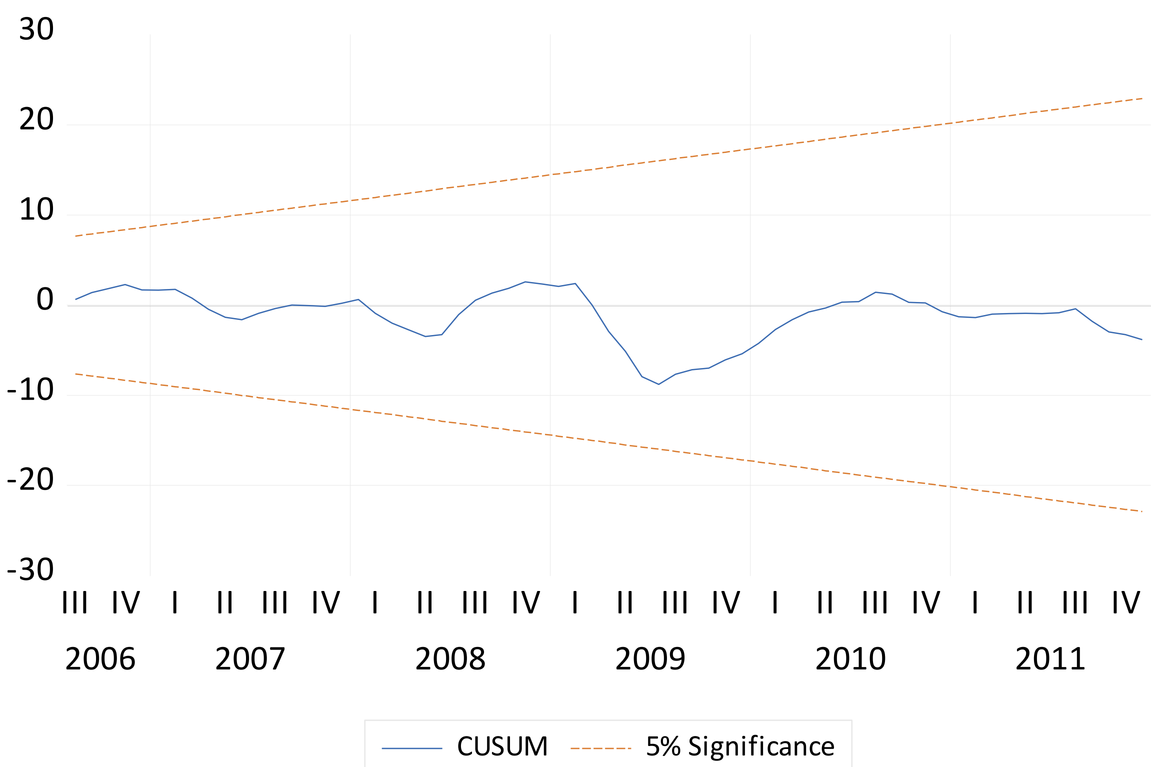
F-statistic	6.546914	Prob. F(4,66)	0.0002
Obs*R-squared	20.16890	Prob. Chi-Square(4)	0.0005
Scaled explained SS	23.49490	Prob. Chi-Square(4)	0.0001

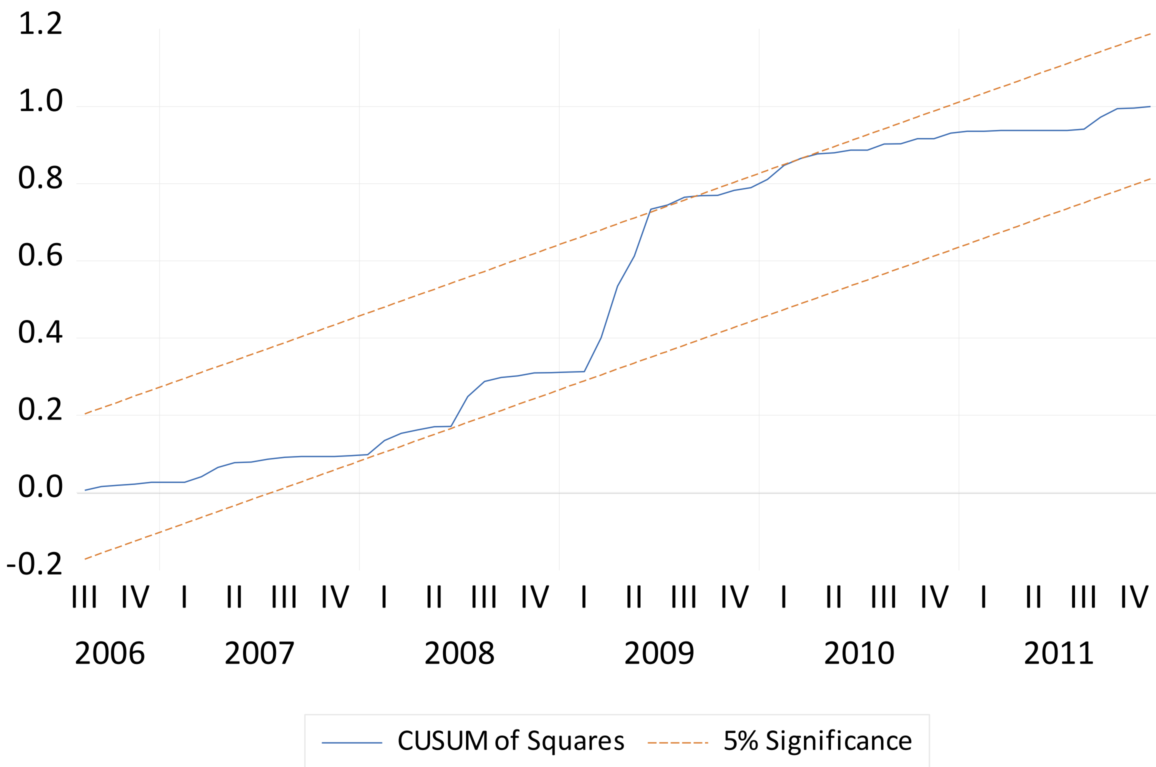
Test Equation:
Dependent Variable: RESID^2

Method: Least Squares
Date: 11/13/18 Time: 14:16
Sample: 2006M02 2011M12
Included observations: 71

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.591309	1.207676	1.317662	0.1922
GDPMP	-0.106930	0.086364	-1.238134	0.2201
INF_S	-0.001797	0.002182	-0.823947	0.4129
UMP_S	-0.005383	0.002600	-2.070079	0.0424
FSI_S_KBD(-1)	0.015313	0.008247	1.856749	0.0678

R-squared	0.284069	Mean dependent var	0.013664
Adjusted R-squared	0.240679	S.D. dependent var	0.022596
S.E. of regression	0.019690	Akaike info criterion	-4.949575
Sum squared resid	0.025588	Schwarz criterion	-4.790231
Log likelihood	180.7099	Hannan-Quinn criter.	-4.886209
F-statistic	6.546914	Durbin-Watson stat	1.397650
Prob(F-statistic)	0.000169		





Appendix A-5-Emerging Africa

Table A- 5: Correlation Analysis for Egypt

```
. correlate fsi_k fsi_e fsi_n fsi_s fsi_eae
(obs=144)

             |    fsi_k    fsi_e    fsi_n    fsi_s  fsi_eae
-------------+---------------------------------------------
       fsi_k |   1.0000
       fsi_e |   0.0529   1.0000
       fsi_n |   0.4688  -0.0205   1.0000
       fsi_s |   0.0157  -0.0947   0.0112   1.0000
     fsi_eae |   1.0000   0.0529   0.4688   0.0157   1.0000
```

Source: Author’s estimation

APPENDIX B: Unit Root Test

Appendix B-1: Panel unit root

Panel unit root test: Summary
Series: ALSI
Date: 01/11/19 Time: 13:01
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.46575	0.6793	4	556
Breitung t-stat	-1.02122	0.1536	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.59042	0.2775	4	556
ADF - Fisher Chi-square	7.65879	0.4675	4	556
PP - Fisher Chi-square	4.30955	0.8282	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(ALSI)
Date: 01/11/19 Time: 13:00
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.11462	0.0000	4	552
Breitung t-stat	-2.76739	0.0028	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-5.77982	0.0000	4	552
ADF - Fisher Chi-square	47.5158	0.0000	4	552
PP - Fisher Chi-square	269.596	0.0000	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

…………………………………..

Panel unit root test: Summary
Series: BDM

Date: 01/11/19 Time: 13:01
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.18415	0.4269	4	556
Breitung t-stat	0.68416	0.7531	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.95877	0.0251	4	556
ADF - Fisher Chi-square	15.3658	0.0524	4	556
PP - Fisher Chi-square	4.49299	0.8101	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(BDM)
Date: 01/11/19 Time: 13:02
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.66366	0.0000	4	552
Breitung t-stat	-4.25073	0.0000	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-6.22557	0.0000	4	552
ADF - Fisher Chi-square	53.3045	0.0000	4	552
PP - Fisher Chi-square	10.6510	0.2223	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

....

Panel unit root test: Summary
Series: EXPR
Date: 01/11/19 Time: 13:02
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Cross-

Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	4.65967	1.0000	4	556
Breitung t-stat	-1.66553	0.0479	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.10497	0.4582	4	556
ADF - Fisher Chi-square	6.95600	0.5414	4	556
PP - Fisher Chi-square	8.52593	0.3838	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(EXPR)
Date: 01/11/19 Time: 13:03
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	5.81205	1.0000	4	552
Breitung t-stat	-5.52661	0.0000	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.97800	0.0000	4	552
ADF - Fisher Chi-square	29.9859	0.0002	4	552
PP - Fisher Chi-square	15.0330	0.0585	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

....

Panel unit root test: Summary
Series: GAP
Date: 01/11/19 Time: 13:03
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.14664	0.1258	4	556
Breitung t-stat	0.27392	0.6079	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.21469	0.0134	4	556
ADF - Fisher Chi-square	24.3437	0.0020	4	556

PP - Fisher Chi-square	3.55384	0.8950	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(GAP)
Date: 01/11/19 Time: 13:03
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	2.31752	0.9898	4	552
Breitung t-stat	-2.69340	0.0035	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.37105	0.0004	4	552
ADF - Fisher Chi-square	26.3585	0.0009	4	552
PP - Fisher Chi-square	6.90240	0.5472	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

....

Panel unit root test: Summary
Series: GDP
Date: 01/11/19 Time: 13:04
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	1.10898	0.8663	4	556
Breitung t-stat	4.27748	1.0000	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.67258	0.7494	4	556
ADF - Fisher Chi-square	10.0638	0.2606	4	556
PP - Fisher Chi-square	4.47904	0.8115	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(GDP)

Date: 01/11/19 Time: 13:04
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.48592	0.0002	4	552
Breitung t-stat	-2.30217	0.0107	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.40872	0.0003	4	552
ADF - Fisher Chi-square	29.1444	0.0003	4	552
PP - Fisher Chi-square	5.32487	0.7224	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

....

Panel unit root test: Summary
Series: INF
Date: 01/11/19 Time: 13:04
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	4.33546	1.0000	4	556
Breitung t-stat	-0.81663	0.2071	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.48291	0.6854	4	556
ADF - Fisher Chi-square	4.65364	0.7939	4	556
PP - Fisher Chi-square	4.67819	0.7914	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(INF)
Date: 01/11/19 Time: 13:05
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Cross-

Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.83011	0.7968	4	552
Breitung t-stat	-2.50599	0.0061	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-5.16429	0.0000	4	552
ADF - Fisher Chi-square	43.2095	0.0000	4	552
PP - Fisher Chi-square	15.3527	0.0526	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

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Panel unit root test: Summary
Series: IPD
Date: 01/11/19 Time: 13:05
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.69821	0.7575	4	556
Breitung t-stat	0.35319	0.6380	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.88722	0.1875	4	556
ADF - Fisher Chi-square	14.2431	0.0756	4	556
PP - Fisher Chi-square	3.63838	0.8882	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(IPD)
Date: 01/11/19 Time: 13:05
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	2.51840	0.9941	4	552
Breitung t-stat	-1.49745	0.0671	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.01675	0.0000	4	552
ADF - Fisher Chi-square	31.7417	0.0001	4	552

PP - Fisher Chi-square	18.2877	0.0192	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

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Panel unit root test: Summary
Series: IRS
Date: 01/11/19 Time: 13:06
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.06000	0.4761	4	556
Breitung t-stat	1.39223	0.9181	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.95212	0.8295	4	556
ADF - Fisher Chi-square	3.80793	0.8740	4	556
PP - Fisher Chi-square	1.74596	0.9878	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(IRS)
Date: 01/11/19 Time: 13:06
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.40704	0.3420	4	552
Breitung t-stat	-2.68113	0.0037	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.53232	0.0000	4	552
ADF - Fisher Chi-square	36.8665	0.0000	4	552
PP - Fisher Chi-square	10.9838	0.2026	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

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Panel unit root test: Summary

Series: LEX
Date: 01/11/19 Time: 13:06
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.75182	0.7739	4	556
Breitung t-stat	0.98725	0.8382	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.22784	0.5901	4	556
ADF - Fisher Chi-square	4.75012	0.7839	4	556
PP - Fisher Chi-square	3.15871	0.9240	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LEX)
Date: 01/11/19 Time: 13:07
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.41147	0.3404	4	552
Breitung t-stat	-1.81478	0.0348	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.64179	0.0041	4	552
ADF - Fisher Chi-square	19.7942	0.0111	4	552
PP - Fisher Chi-square	6.83290	0.5548	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

....

Panel unit root test: Summary
Series: LIR
Date: 01/11/19 Time: 13:07
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	1.08168	0.8603	4	556
Breitung t-stat	-0.71971	0.2359	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.12730	0.4494	4	556
ADF - Fisher Chi-square	5.65882	0.6854	4	556
PP - Fisher Chi-square	3.06522	0.9302	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LIR)
Date: 01/11/19 Time: 13:07
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.43833	0.0752	4	552
Breitung t-stat	-4.05039	0.0000	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.75661	0.0000	4	552
ADF - Fisher Chi-square	45.2287	0.0000	4	552
PP - Fisher Chi-square	61.6841	0.0000	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

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Panel unit root test: Summary
Series: LNALSI
Date: 01/11/19 Time: 13:08
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.02793	0.4889	4	556
Breitung t-stat	-1.63647	0.0509	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.17906	0.1192	4	556

ADF - Fisher Chi-square	10.6936	0.2197	4	556
PP - Fisher Chi-square	5.77248	0.6727	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNALSI)
Date: 01/11/19 Time: 13:08
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.51768	0.0645	4	552
Breitung t-stat	-3.60376	0.0002	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-5.82361	0.0000	4	552
ADF - Fisher Chi-square	47.5947	0.0000	4	552
PP - Fisher Chi-square	276.818	0.0000	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

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Panel unit root test: Summary
Series: NPLS
Date: 01/11/19 Time: 13:08
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.56756	0.0585	4	556
Breitung t-stat	2.83160	0.9977	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.78106	0.0375	4	556
ADF - Fisher Chi-square	18.0944	0.0205	4	556
PP - Fisher Chi-square	21.9060	0.0051	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary

Series: D(NPLS)
Date: 01/11/19 Time: 13:08
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.17674	0.0000	4	552
Breitung t-stat	-4.87331	0.0000	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.20511	0.0000	4	552
ADF - Fisher Chi-square	76.7115	0.0000	4	552
PP - Fisher Chi-square	11.5306	0.1734	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

....

Panel unit root test: Summary
Series: RIR
Date: 01/11/19 Time: 13:09
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	5.37967	1.0000	4	556
Breitung t-stat	-1.43793	0.0752	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.30445	0.6196	4	556
ADF - Fisher Chi-square	7.89206	0.4441	4	556
PP - Fisher Chi-square	9.60273	0.2940	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(RIR)
Date: 01/11/19 Time: 13:09
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	4.06151	1.0000	4	552
Breitung t-stat	-5.34606	0.0000	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-7.06791	0.0000	4	552
ADF - Fisher Chi-square	63.6754	0.0000	4	552
PP - Fisher Chi-square	16.9879	0.0302	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

....

Panel unit root test: Summary
Series: UMP
Date: 01/11/19 Time: 13:09
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.22091	0.4126	4	556
Breitung t-stat	0.26553	0.6047	4	552
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.85761	0.8044	4	556
ADF - Fisher Chi-square	4.34443	0.8248	4	556
PP - Fisher Chi-square	1.82518	0.9859	4	572

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(UMP)
Date: 01/11/19 Time: 13:10
Sample: 2006M01 2017M12
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 4
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	1.09170	0.8625	4	552
Breitung t-stat	-2.08721	0.0184	4	548
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.59169	0.0002	4	552

ADF - Fisher Chi-square	30.6805	0.0002	4	552
PP - Fisher Chi-square	9.74366	0.2835	4	568

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix B-2: Individual Unit Root Test Result

Egypt

Null Hypothesis: ALSI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.361617	0.8680
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(ALSI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.26870	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: BDM has a unit root
Exogenous: None
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.043208	0.2666
Test critical values:	1% level	-2.581584	
	5% level	-1.943123	
	10% level	-1.615200	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(BDM) has a unit root
Exogenous: None
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*

Augmented Dickey-Fuller test statistic		-3.201145	0.0016
Test critical values:	1% level	-2.583011	
	5% level	-1.943324	
	10% level	-1.615075	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: CBPR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.754318	0.9664
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(CBPR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.71434	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: E3MTB has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.048785	0.5693
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(E3MTB) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.488334	0.0000
Test critical values:	1% level	-4.023975	

	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: EBR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.308299	0.4264
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EBR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.89626	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: EXPR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.765542	0.7162
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXPR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.740066	0.0229
Test critical values:	1% level	-4.025924	
	5% level	-3.442712	
	10% level	-3.146022	

*MacKinnon (1996) one-sided p-values.
Null Hypothesis: GAP has a unit root
Exogenous: None
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.823885	0.0650
Test critical values:	1% level	-2.581584	
	5% level	-1.943123	
	10% level	-1.615200	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.918640	0.1599
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GAP) has a unit root
Exogenous: None
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.769091	0.0059
Test critical values:	1% level	-2.581584	
	5% level	-1.943123	
	10% level	-1.615200	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GDP has a unit root
Exogenous: None
Lag Length: 13 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.168732	0.9372
Test critical values:	1% level	-2.582872	
	5% level	-1.943304	
	10% level	-1.615087	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GDP) has a unit root
Exogenous: None
Lag Length: 13 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.930748	0.0514
Test critical values:	1% level	-2.583011	
	5% level	-1.943324	
	10% level	-1.615075	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IBR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.672855	0.9996
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IBR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.33226	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: INF has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.889050	0.3293
Test critical values:	1% level	-2.581349	
	5% level	-1.943090	
	10% level	-1.615220	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(INF) has a unit root

Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.124749	0.0327
Test critical values:	1% level	-2.581466	
	5% level	-1.943107	
	10% level	-1.615210	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IPD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.200522	0.4852
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IPD) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.429917	0.0516
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IRS has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.346672	0.5585
Test critical values:	1% level	-2.581827	
	5% level	-1.943157	
	10% level	-1.615178	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IRS) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.845167	0.0621
Test critical values:	1% level	-2.581827	
	5% level	-1.943157	
	10% level	-1.615178	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LEX has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.788863	0.8822
Test critical values:	1% level	-2.581349	
	5% level	-1.943090	
	10% level	-1.615220	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LEX) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.715287	0.0817
Test critical values:	1% level	-2.581349	
	5% level	-1.943090	
	10% level	-1.615220	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.748395	0.2192
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LIR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*

Augmented Dickey-Fuller test statistic		-4.253074	0.0050
Test critical values:	1% level	-4.030729	
	5% level	-3.445030	
	10% level	-3.147382	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: NPLS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.231083	0.4684
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(NPLS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.975569	0.0000
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: RIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.976228	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(RIR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.834591	0.0175
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.
Null Hypothesis: UMP has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.678519	0.8612
Test critical values:	1% level	-2.581827	
	5% level	-1.943157	
	10% level	-1.615178	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(UMP) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.404174	0.0162
Test critical values:	1% level	-2.581827	
	5% level	-1.943157	
	10% level	-1.615178	

*MacKinnon (1996) one-sided p-values.

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Null Hypothesis: ALSI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.647397	0.7691
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(ALSI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.58519	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: BDM has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.622486	0.4684
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(BDM) has a unit root
Exogenous: Constant
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.037416	0.0017
Test critical values:	1% level	-3.481623	
	5% level	-2.883930	
	10% level	-2.578788	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: EXH has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 6 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.666531	0.2522
Test critical values:	1% level	-4.026429	
	5% level	-3.442955	
	10% level	-3.146165	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXH) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-7.148540	0.0000

Test critical values:	1% level	-4.024452	
	5% level	-3.442006	
	10% level	-3.145608	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: EXPR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.097648	0.5422
Test critical values:	1% level	-4.025924	
	5% level	-3.442712	
	10% level	-3.146022	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXPR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.441746	0.0000
Test critical values:	1% level	-4.024452	
	5% level	-3.442006	
	10% level	-3.145608	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GAP has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.537206	0.5119
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GAP) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.449487	0.0109
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GDP has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.599770	0.8659
Test critical values:	1% level	-3.477487	
	5% level	-2.882127	
	10% level	-2.577827	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GDP) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.591173	0.0972
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IBR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.183905	0.0919
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IBR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.446915	0.0000
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: INF has a unit root

Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.259395	0.4529
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(INF) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.093280	0.0000
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IPD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.994071	0.5991
Test critical values:	1% level	-4.025924	
	5% level	-3.442712	
	10% level	-3.146022	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IPD) has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.885120	0.0497
Test critical values:	1% level	-3.478189	
	5% level	-2.882433	
	10% level	-2.577990	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IRS has a unit root
Exogenous: Constant

Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.202678	0.6724
Test critical values:	1% level	-3.477487	
	5% level	-2.882127	
	10% level	-2.577827	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IRS) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.710286	0.0049
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: KBR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.408125	0.0543
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(KBR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.41734	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*

Augmented Dickey-Fuller test statistic		-2.748395	0.2192
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LIR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.253074	0.0050
Test critical values:	1% level	-4.030729	
	5% level	-3.445030	
	10% level	-3.147382	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: NPL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.097891	0.1109
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(NPL) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.244381	0.0001
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: RIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.413819	0.8529
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(RIR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.593896	0.0000
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: UMP has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.390580	0.7953
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(UMP) has a unit root
Exogenous: None
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.439399	0.0147
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Nigeria

Null Hypothesis: ALSI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.639015	0.7726
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(ALSI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.20547	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: BDM has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.731388	0.2258
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(BDM) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.507172	0.0000
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: CBPR has a unit root
Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.994848	0.5988
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(CBPR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.88550	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: EXCH has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.205258	0.9721
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXCH) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.112415	0.0279
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: EXPR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.373240	0.3919
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXPR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.225248	0.0054
Test critical values:	1% level	-4.025924	
	5% level	-3.442712	
	10% level	-3.146022	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GAP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.493437	0.8275
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GAP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.069005	0.0088
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.105845	0.9971
Test critical values:	1% level	-4.025426	

	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.827857	0.0007
Test critical values:	1% level	-4.030729	
	5% level	-3.445030	
	10% level	-3.147382	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IBR has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.485854	0.5039
Test critical values:	1% level	-2.581827	
	5% level	-1.943157	
	10% level	-1.615178	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IBR) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.121972	0.0000
Test critical values:	1% level	-2.581827	
	5% level	-1.943157	
	10% level	-1.615178	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: INF has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 6 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.087955	0.5475
Test critical values:	1% level	-4.026429	
	5% level	-3.442955	
	10% level	-3.146165	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(INF) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.452500	0.0026
Test critical values:	1% level	-4.030729	
	5% level	-3.445030	
	10% level	-3.147382	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IPD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.486831	0.3342
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IPD) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.607259	0.0015
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IRS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.189038	0.4915
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IRS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.733655	0.0010
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.538422	0.3094
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LIR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.778100	0.0000
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: NPLS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.885164	0.6569
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(NPLS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-5.619309	0.0000

Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: RIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.517646	0.3193
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(RIR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.446750	0.0000
Test critical values:	1% level	-4.030729	
	5% level	-3.445030	
	10% level	-3.147382	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: TBR has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.997204	0.2847
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	
	10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(TBR) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.74745	0.0000
Test critical values:	1% level	-2.581349	
	5% level	-1.943090	
	10% level	-1.615220	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: UMP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.377958	0.8633
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(UMP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.259742	0.0778
Test critical values:	1% level	-4.030729	
	5% level	-3.445030	
	10% level	-3.147382	

*MacKinnon (1996) one-sided p-values.

South Africa

Null Hypothesis: ALSI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.178615	0.4974
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(ALSI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.70021	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: BDM has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.737452	0.2234
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(BDM) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.902061	0.0000
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: CBPR has a unit root

Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.176601	0.4985
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(CBPR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.038564	0.0096
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: EXCH has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.077071	0.9262
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXCH) has a unit root
Exogenous: None
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.235775	0.0250
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: EXPR has a unit root
Exogenous: Constant, Linear Trend

Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.716709	0.2316
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(EXPR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.085535	0.0083
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GAP has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.970822	0.2994
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GAP) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.323374	0.0157
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.207163	0.9047

Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.
Null Hypothesis: D(GDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.659985	0.0012
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.
Null Hypothesis: INF has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.242443	0.4621
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(INF) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.138923	0.0000
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IPD has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.189527	0.9359
Test critical values:	1% level	-3.477144	
	5% level	-2.881978	
	10% level	-2.577747	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IPD) has a unit root

Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.192469	0.0000
Test critical values:	1% level	-3.477144	
	5% level	-2.881978	
	10% level	-2.577747	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: IRS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.722319	0.7363
Test critical values:	1% level	-4.024452	
	5% level	-3.442006	
	10% level	-3.145608	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(IRS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.787855	0.0000
Test critical values:	1% level	-4.024452	
	5% level	-3.442006	
	10% level	-3.145608	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.821954	0.9604
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LIR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*

Augmented Dickey-Fuller test statistic		-5.526593	0.0000
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: NPLS has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.348440	0.1585
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(NPLS) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.316649	0.0006
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: RIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.933709	0.9483
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(RIR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.828777	0.0000

Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: S3MTB has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.297521	0.4322
Test critical values:	1% level	-4.024935	
	5% level	-3.442238	
	10% level	-3.145744	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(S3MTB) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.032505	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: SGB has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.003001	0.1351
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(SGB) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.57919	0.0000
Test critical values:	1% level	-4.023975	
	5% level	-3.441777	
	10% level	-3.145474	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: UMP has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.318101	0.9180
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(UMP) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.361900	0.0140
Test critical values:	1% level	-3.477835	
	5% level	-2.882279	
	10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Appendix C

Appendix C-1: VAR Residual Serial Correlation LM Tests

Date: 01/17/19 Time: 07:32						
Sample: 2006M01 2017M12						
Included observations: 560						
Null hypothesis: No serial correlation at lag h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	192.4226	81	0.0000	2.4167	(81, 3279.0)	0.0000
2	268.7192	81	0.0000	3.414409	(81, 3279.0)	0.0000
3	102.068	81	0.0569	1.264446	(81, 3279.0)	0.0569

4	44.87154	81	0.9996	0.551093	(81, 3279.0)	0.9996

Table 2: Diagnostics; Heteroskedasticity Tests

VAR Residual Heteroskedasticity Tests (Levels and Squares)			VAR Residual Heteroskedasticity Tests (Includes Cross Terms)		
Date: 01/17/19 Time: 07:26			Date: 01/17/19 Time: 07:28		
Sample: 2006M01 2017M12			Sample: 2006M01 2017M12		
Included observations: 560			Included observations: 560		
Joint test:			Joint test:		
Chi-sq	df	Prob.	Chi-sq	df	Prob.
7548.939	3150	0	24437.66	16335	0

Appendix D

Appendix D-1: Mean Group Result for Model One

	Mean group estimation						
	D.npls	Coef.	Std.	Err.	z P>z	[95%	Conf.Interval]
ECT	gap	-8.08781	10.4224	-0.78	0.438	-28.5153	12.33972
	inf	-261.795	170.9424	-1.53	0.126	-596.836	73.2455
	ump	-19.7223	22.35749	-0.88	0.378	-63.5422	24.0976
SR	ECT	-0.02298	0.016346	-1.41	0.16	-0.05501	0.009061
	gap						
	D1.	-0.22188	0.333969	-0.66	0.506	-0.87644	0.432692
	inf_2						

	D1.	2.256585	3.043182	0.74	0.458	-3.70794	8.221111
	ump						
	D1.	0.835509	1.102393	0.76	0.449	-1.32514	2.99616
	_cons	0.518121	0.708444	0.73	0.465	-0.8704	1.906644

Appendix D-2: Full PMG Result for Model One

		Pooled mean group estimation						
		D.npls	Coef.	Std.	Err.	z P>z	[95%	Conf.Interval]
LR	ECT							
		gap	0.363747	0.230263	1.58	0.1140	-0.08756	0.815054
		inf_2	-16.3937	4.95374	-3.31	0.0010	-26.1029	-6.68457
		ump	-0.67785	0.190384	-3.56	0.0000	-1.051	-0.30471
SR	c_id_1_EGYPT							
		ECT	-0.01834	0.004299	-4.27	0.0000	-0.02677	-0.00992
		gap						
		D1.	0.217076	0.10051	2.16	0.0310	0.020081	0.414072
		inf_2						
		D1.	10.59232	1.514208	7	0.0000	7.624525	13.56011
		ump						
		D1.	-0.21684	0.130603	-1.66	0.0970	-0.47281	0.03914
		_cons	0.278361	0.09824	2.83	0.0050	0.085814	0.470908
	c_id_2_KENYA							
		ECT	-0.08517	0.00815	-10.45	0.0000	-0.10114	-0.0692
		gap						
		D1.	-0.09911	0.218326	-0.45	0.6500	-0.52702	0.3288

		inf_2						
		D1.	-4.86283	2.23558	-2.18	0.0300	-9.24448	-0.48117
		ump						
		D1.	0.020401	1.413569	0.01	0.9880	-2.75014	2.790945
		_cons	1.20726	0.205351	5.88	0.0000	0.80478	1.609741
	c_id_3_NIGERIA							
		ECT	-0.00395	0.00936	-0.42	0.6730	-0.02229	0.014398
		gap						
		D1.	-0.41023	0.652723	-0.63	0.5300	-1.68955	0.869079
		inf_2						
		D1.	-1.44246	14.42088	-0.1	0.9200	-29.7069	26.82195
		ump						
		D1.	2.363269	1.423544	1.66	0.0970	-0.42683	5.153365
		_cons	-0.03186	0.156351	-0.2	0.8390	-0.33831	0.274577
	c_id_4_SA							
		ECT	-0.02755	0.003682	-7.48	0.0000	-0.03476	-0.02033
		gap						
		D1.	-0.28139	0.045901	-6.13	0.0000	-0.37136	-0.19143
		inf_2						
		D1.	1.196674	1.060673	1.13	0.2590	-0.88221	3.275555
		ump						
		D1.	0.23839	0.126098	1.89	0.0590	-0.00876	0.485538
		_cons	0.554492	0.149934	3.7	0.0000	0.260626	0.848358

Appendix D-3: Mean Group Result for Model Two

	Mean group estimation						
	D.npls	Coef.	Std.	Err.	z P>z	[95%	Conf.Interval]
ECT	lnalsi	62.64317	38.34211	1.63	0.1020	-12.506	137.7923
	ibr	1.242567	1.709979	0.73	0.4670	-2.10893	4.594065
	lex	-39.5457	30.46185	-1.3	0.1940	-99.2498	20.15847
SR	ECT	-0.01843	0.012384	-1.49	0.1370	-0.0427	0.005846
	lnalsi						
	D1.	-0.36615	0.302887	-1.21	0.2270	-0.9598	0.227495
	ibr						
	D1.	-0.01467	0.002792	-5.25	0.0000	-0.02014	-0.0092
	lex						
	D1.	23.81122	16.53451	1.44	0.1500	-8.59583	56.21826
	_cons	-2.45373	1.742135	-1.41	0.1590	-5.86825	0.960795

Appendix D.4: Full PMG Result for Model Two

	Pooled mean group estimation						
	D.npls	Coef.	Std.	Err.	z P>z	[95%	Conf.Interval]
ECT	lnalsi	4.934964	1.847091	2.67	0.0080	1.314732	8.555196
	ibr	3.211207	0.521997	6.15	0.0000	2.18811	4.234303
	lex	-3.27762	2.060253	-1.59	0.1120	-7.31564	0.760406
	c_id_1						
	ECT	-0.0027	0.001463	-1.85	0.0640	-0.00557	0.000163
	lnalsi						
	D1.	-0.15402	0.130776	-	0.239	-0.41033	0.102299

				1.18			
	ibr						
	D1.	-0.00926	0.017111	- 0.54	0.5880	-0.0428	0.024277
	lex						
	D1.	2.346569	0.854762	2.75	0.006	0.671266	4.021872
	_cons	-0.22233	0.076089	- 2.92	0.003	-0.37146	-0.0732
	c_id_2						
	ECT	-0.01561	0.003043	- 5.13	0.0000	-0.02158	-0.00965
	lnalsi						
	D1.	-0.2544	0.561795	- 0.45	0.651	-1.3555	0.846702
	ibr						
	D1.	-0.01409	0.01459	- 0.97	0.334	-0.04269	0.014505
	lex						
	D1.	52.09628	6.574196	7.92	0.0000	39.21109	64.98147
	_cons	-0.66237	0.092539	- 7.16	0.0000	-0.84374	-0.481
	c_id_3						
	ECT	-0.00508	0.003026	- 1.68	0.093	-0.01101	0.000849
	lnalsi						
	D1.	-0.78897	0.989967	-0.8	0.425	-2.72927	1.151326

Appendix D-5: Hausman Test for Model One

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	Coefficients (b) mg	(B) pmg	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
gap	-8.087807	.363747	-8.451554	11.37312
inf_2	-261.7954	-16.39372	-245.4016	186.508
ump	-19.72228	-.6778509	-19.04443	24.40118

```
                  b = consistent under Ho and Ha; obtained from xtpmg
   B = inconsistent under Ha, efficient under Ho; obtained from xtpmg

Test:  Ho:  difference in coefficients not systematic

             chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                     =        4.19
           Prob>chi2 =      0.2412
```

Appendix D-6: Hausman Test for Model Two

.

	Coefficients (b) mg	(B) pmg	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
lnalsi	62.64317	4.934964	57.70821	63.00835
ibr	1.242567	3.211207	-1.968639	2.762362
lex	-39.54566	-3.277615	-36.26805	50.03767

```
                  b = consistent under Ho and Ha; obtained from xtpmg
   B = inconsistent under Ha, efficient under Ho; obtained from xtpmg

Test:  Ho:  difference in coefficients not systematic

             chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                     =        0.85
           Prob>chi2 =      0.8383
```