Stochastic Modelling in Financial Markets: Case Study of the Nigerian Stock Market

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DECLARATION

I certify that the substance of this thesis has not been already submitted for any degree and is not currently being submitted for any other degree. I also certify that to the best of my knowledge any assistance received in preparing this thesis, and all sources used, have been acknowledged and referenced in this thesis.

ABSTRACT

Stochastic Models in Financial Market Analysis: A Case Study of the Nigerian Stock Market (NSM)

This research uses suitable stochastic models typically encountered in empirical and quantitative financial economics to analyse stock market data from the Nigerian Stock Market (NSM), in light of a) possible changes in the policy environments as result of the 2004 financial reforms by the then Governor of Central Bank of Nigeria, b) effects or otherwise of the 2008-09 global financial crises on the Nigerian financial system, and c) more technical issues underpinning performance of financial markets for example market efficiency, anomalies, bubbles, volatilities and their implications for investment decisions, stock market development and financial policy.

There are substantial differences in the operation and characteristics of developed, emerging and pre-emerging (African) financial markets in terms of the above mentioned issues. Sometimes as part of general discussion of results we comment on the extent to which the characteristics of the NSM differ from known results in developed markets.

A wide range of financial econometric methods and models including multivariate regression, Goodness of fit tests, Runs, Autocorrelation Function, Variance Ratio, Autoregressive tests, and discrete log logistic and GARCH-type models are applied. Both the All Share index and return data for 2000 to 2010 are used in this study. The time series data are divided into two periods namely pre-reforms (2000-2004) and post-reforms (2005-2010).

This study provides both investors and researchers in emerging African markets with a clear understanding of key financial characteristics of the NSM. Some useful results were obtained. Key characteristics of the NSM analysed in terms of market index prices and returns reveal evidence of market inefficiency and volatility. The data do not provide evidence of bubbles and anomalies in the NSM.

This study, according to the author's best knowledge, is possibly the most comprehensive combined study of crucial issues affecting the NSM including volatility, anomalies, bubbles and market efficiency. However, some other issues are excluded from the study because of the limitations of the data for example valuations and predictability, which are more suitably studied within specific companies and market sectors.

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First and foremost, I thank the Almighty Allah for giving me the opportunity and the ability to accomplish this work. Without Allah's help and guidance, I would not have reached to this point.

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Mahmoud Abdulsalam Altayeb

DEDICATION

This dissertation is dedicated to

My beloved mother and father, Fdela and Abdulsalam,

My mother in law, Fatema

My wonderful wife, Seham

My lovely children: Mohammed, Abdulsalam, and Ayoub

My Brothers and Sisters

and

All Altayeb's Family

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ABBREVIATIONS

AFDB	African Development Bank
AFEM	Autonomous Foreign Exchange Market
APT	Arbitrage Pricing Theory
BRIC	Countries of Brazil, Russia, India and China
CAGR	Compound Annual Growth Rate
CAPM	Capital Asset Pricing Model
CBN	Central Bank of Nigeria
EEEM	Eastern European Emerging Markets
EMH	Efficient Market Hypothesis
FDI	Foreign Direct Investment
FMBN	Federal Mortgage Bank of Nigeria
FMF	Federal Ministry of Finance
FSRCC	Financial Services Regulatory Coordinating Committee
GCC	Gulf Cooperation Council
GDP	Gross Domestic Product
GFD	Global Financial Data
GSM	Ghana Stock Market
i.i.d	independent and identically distributed
IFC	International Finance Corporation
IFEM	Inter-bank foreign exchange market
IMF	International Monetary Fund
MENA	Middle East and North African
NBCB	National Board for Community Banks
NDIC	Nigeria Deposit Insurance Corporation
NEEDS	National Economic Empowerment and Development Strategy
NFS	Nigerian Financial System
NIC	National Insurance Commission
NSE	Nigerian Stock Exchange
NSM	Nigerian Stock Market
OIC	Organisation of the Islamic Conference
PMIs	Primary Mortgage Institutions
QMS	Quantitative Micro Software
RWT	Random Walk Theory
SEC	Securities and Exchange Commission
SFEM	The Second-tier Foreign Exchange Market
SSA	Sub-Sahara African
UNECA	United Nations Economic Commission for Africa
VLIS	Value Line Investment Survey
WB	World Bank
WDAS	Wholesale Dutch Auction System

CHAPTER 1: INTRODUCTION

1.1 Introduction

There has been a growing interest in the analysis of financial markets using a number of techniques related to stochastic processes and applied statistical modelling. These techniques are broadly referred to as empirical finance or applied financial economics. Most of these techniques of financial market analysis have been based mainly on the characteristics of developed economies. As noted by Islam and Watanapalachaikul (2005, p. 1), it is of interest to apply these techniques to developing economies in order to better understand the stock market characteristics of these economies and the implications of the characteristics for investment decisions of market participants and financial policy.

It is known from literature that the market characteristics and operations of developing and emerging financial markets are different from those of developed economies. For example, developing financial markets are relatively unstable, underdeveloped, inefficient, and more volatile compared to developed financial markets, Bekaert and Harvey (2002).

Currently, there are limited numbers of comprehensive studies of the empirical characteristics of developing economies based on a number of key issues such as market efficiency, bubbles, anomalies, volatility, predictability and valuation. Existing studies concentrate mainly on one issue at a time and focus more on emerging Asian markets, the BRIC countries (Brazil, Russia, India and China) and other South American countries. Such studies are rare in African financial markets.

Therefore, this thesis undertakes a comprehensive analysis of the empirical characteristics of one of the four largest financial markets in Africa, the Nigerian Stock Market (NSM). The study is comprehensive in the sense that it investigates some of the key issues in financial markets listed above namely, market efficiency, bubbles, anomalies and volatility, using the NSM as a case study.

These issues are discussed in Islam and Watanapalachaikul (2005) with respect to the Thai Stock Market. The different models and approaches used in studying the issues are also examined in Cuthbertson and Nitsche (2005). This study aims to apply the models and approaches to the NSM.

This chapter introduces the research, explains the research aims and objectives, discusses the rationale for the research, and provides a background for the study.

1.2 Rationale for Research

As mentioned above, the key rationales for this study are as follow. Firstly, there is limited research on the characteristics of financial markets in Africa. Secondly, although some studies of financial markets in Africa investigate particular issues singly, there is no comprehensive study of the key issues together using data from the same financial market. Studying the issues together in this way will provide a fuller understanding of the characteristics and behaviours of the financial market. This study explores these issues using data from the NSM; the particular issues studied are market efficiency, bubbles, anomalies and volatility.

Nigeria embarked on financial reforms of banks and related financial institutions in 2004 and the Nigerian financial system and stock market were affected by the 2007-08 global financial crises. The research therefore compares the behaviours of the NSM in both the pre- and post-reform and pre- and post-crisis periods as revealed by the key issues studied. Thus, understanding the effect of the reforms and financial crisis on the dynamics of the NSM will facilitate effective financial policy and stock market development in Nigeria.

As we will explain later in this thesis, knowledge of the underlying characteristics of the NSM across different policies and reforms will benefit investors and policy makers. It will enable the investors to improve their investment and risk management strategies. For instance, investors will understand to what extent the market is or is not efficient, whether there are high levels of bubbles in the market which will distort asset prices, similarly whether the market is highly volatile and riskier to invest in, and what anomalies exist in the market, which they can avoid or benefit from as they play the market. We emphasise that all these issues are related to market efficiency, in the sense that if a market is efficient in some sense (weak, semi-strong or strong) then all market participants have access to important information on asset prices, so that investors without enough information will not be disadvantaged in their market decisions.

The knowledge will also enable financial policy makers to improve the overall performance and operations of the stock market, by implementing policies that will ultimately make the market more efficient, less prone to bubbles, and less volatile, for instance.

By using appropriate statistical and empirical finance models to study the issues and characteristics of the NSM as a case study, the research contributes to the literature base on quantitative modelling of African stock markets.

The Libyan stock market is a new emerging market in the North African region. The researcher is a Libyan national and it is hoped that experiences gained from this research will facilitate understanding of how the same issues apply to the Libyan stock market.

1.3 Rationale for choosing NSM as a case study:

Nigerian Stock Market is particularly interesting as a case study because it is one of the four largest African Stock Markets, namely South Africa, Algeria, Nigeria and Egypt, as has been noted by African development Bank (AFDB, 2007). According to International Monetary Fund (IMF) (2008), "*Nigeria's recent private sector-led growth and vibrant capital markets with potentials for investors have placed it in a league of eight sub-Saharan African countries (outside South Africa), heading towards emerging market status*", quoted by Aledare et al (2008, p. 2)

Nigerian Stock Market has undergone powerful reforms since it has been established in 1960 and as a result of that it became one of the fourth largest stock market in Africa. Ikokwu (2008) notes that the country is now a "frontier emerging market". Nigerian banks raised about $12 billion in capital over 2006-07 mostly from offshore investors, Ikokwu (2008).

There are significant differences between the Nigerian stock market and other stock markets in its neighbouring countries, in terms of market indicators such as number of listed companies, market capitalization, and accessibility to foreign investors. But in general, there are some factors preventing the development of NSM. Prominent among these factors are: deficiencies in the legal framework governing NSM, the small number of listed companies, undiversified investment instruments, market illiquidity, the lack of market depth, high concentration of listed stocks in a few sectors for example banking, market, poor investor awareness in general, and in many cases lack of economic stability.

The above traits make the research in the NSM and the Nigerian financial development very interesting. It also means that the results from the research will be useful in supporting other African markets as they develop for example the Libyan Stock Market, which is still very new.

1.4 Brief Background on the Nigerian Financial System and Stock Market

The Nigerian financial system comprises bank and non-bank financial institutions which are regulated by the Federal Ministry of Finance (FMF), Central Bank of Nigeria (CBN), Nigeria Deposit Insurance Corporation (NDIC), Securities and Exchange Commission (SEC), National Insurance Commission (NIC), Federal Mortgage Bank of Nigeria (FMBN), Stock Market Exchange and the National Board for Community Banks (NBCB) (Nigerian embassy in Netherlands official site 2008).

The Nigerian Stock Exchange (NSE) was established in 1960 as the Lagos Stock Exchange. In December 1977, it became the Nigerian Stock Exchange that has different branches established in some of the major commercial cities all over the country. At present, there are eight branches of The Nigerian Stock Exchange. The branch of Lagos was opened in 1960; Kaduna, 1978; Port Harcourt, 1980; Kano, 1989; Onitsha, February 1990; and Ibadan August 1990; Abuja, October 1999 and Yola, April 2002 respectively. Lagos is the Head Office of The Exchange and a new office for commodities trading has just been opened in Abuja. Each branch has a trading floor (NSE web-page 2008).

The NSE started to operate in 1960 with 19 securities listed for trading. By the end of 2010 the total market value of 264 securities listed on the Exchange increased by 41.12%, from N7.03 trillion to N9.92 trillion at year-end. The increase in market capitalization resulted mainly from equity price appreciation. By year-end, the market capitalization of the 217 listed equities was N7.92 trillion; seventeen subsectors recorded increased market capitalization of between 3.9% and 622.05%, while sixteen subsectors suffered a reduction in market capitalization of between 2.8% and 48%.[1]

[1] http://dapocosby.blogspot.co.uk/2011/01/nigerian-stock-exchange-review-of.html#!/2011/01/nigerian-stock-exchange-review-of.html

The market has in place a tested network of Stockbrokerage Firms, Issuing Houses (Merchant Banks), practicing corporate law firms and over 50 quality firms of auditors and reporting accountants (most with international links).

1.5 Research Issues

As earlier noted, this study aims to evaluate NSM using some current stochastic and applied statistical models used in studying the movements, prices and volatilities of financial securities in global financial markets by studying the key issues for stock market such as volatilities, market efficiency, anomalies etc. The chosen techniques will be used to study the key issues addressed earlier.

1.5.1 Objectives of the research

The specific objectives of the research are as follow:

1. To critically review the literature bases on stochastic and applied statistical models used to predict movements of financial securities in stock markets for example stock market returns, asset prices, market indices and risks. The focus will be on techniques used in the analysis of movements of stock prices, indices and returns.

2. To explore the suitability of these models and techniques for analyzing data collected from the Nigerian Stock Market (NSM), especially with respect to key issues and characteristics of financial markets indicated above for example market efficiency, volatility, anomalies etc.

3. To briefly discuss the implications of the results obtained from 1 and 2 above for stock market development and financial policy.

Based on the selected issues of interest, the following research questions are addressed:

1. Is the Nigerian Stock Market (NSM) efficient, at least in the weak-form sense of Efficient the Market Hypothesis (as will be discussed in chapter 3)?

2. Is there any evidence of speculative bubbles in the NSM?

3. Are there any anomalies in the behaviour of the NSM data for example calendar effects on the stock market returns?

4. Is NSM characterized by excessive volatility of returns?

5. How do the results of the research compare for periods before and after the reforms and also for periods before and after the global financial crisis?

6. What are implications of the research results for investment strategy, stock market development and financial policy in Nigeria?

1.6 Indicative Structure of the thesis:

The thesis is divided into ten chapters. Chapter 1 provides an overview of the context and justification of this research. The chapter begins with background information on the research, provides the rationale of the study and a brief background of Nigerian financial system and stock market.

Chapter 2 presents a general background on emerging financial market with more focus on Nigerian Stock Market (NSM). The chapter also presents the structure and characteristics of the Nigerian financial system.

Chapter 3 provides an overall literature review of different aspects of the study related to the objectives and research questions.

Chapter 4 examines the research methodologies and presents the justifications for selected models used in the study. Data collection and sampling are also looked at in this chapter.

Chapter 5 gives the descriptive statistics and general characteristics of the data collected from the NSM case study.

Chapters 6 to 9 apply appropriate models to the specific issues and characteristics of the NSM namely market efficiency, speculative bubbles, anomalies and volatility.

Chapter 10 summarises the research findings, including the implications of the research for financial policy and stock market development in Nigeria (already discussed in various chapters), and concludes the thesis. The chapter also summarises the main contributions of the research to knowledge.

CHAPTER 2: GENERAL BACKGROUND ON NIGERIAN FINANCIAL SYSTEM AND STOCK MARKET (NSM)

2.1 Introduction

A stock market in general refers to a financial market where buyers and sellers trade in company stocks and other securities which are listed in the stock market. Stock market plays a pivotal role in the financial market, as explained in Chapter 1, where we discussed the rationale for understanding key characteristics of stock market behaviour for example market efficiency, bubbles, volatility and anomalies.

This chapter describes the Nigerian financial system and stock market within the context of emerging financial markets. The specific objectives of the chapter are as follows:

- To discuss relevant characteristics of emerging markets and relate the characteristics to emerging African markets and the Nigerian financial market in particular
- To provide an overview of the importance of stock markets to economic development for example the links between stock markets, economic growth, investments in a financial system and asset pricing, risks and returns
- To present background information on the Nigerian financial system, including the Nigerian Stock Market (NSM), which is of direct interest in this research.

The background information provides a broad understanding of the economic situation of Nigeria before and after the 2004 financial reforms and the 2007 global financial crisis. As mentioned earlier in Chapter 1, this understanding is particularly important for explaining the implication of the research findings for investments in the NSM, stock market development and financial policy making (Objective 3 of the research).

This chapter, therefore, motivates the research by describing key features of the NSM and the changing contexts of financial regulations and reforms across different periods of study, namely pre- and post-reforms and pre-and post-crisis. This will enable us compare the effects of the reforms and global financial crisis on the stock market, and thereby facilitate more effective development of the NSM.

2.2 Characteristics of Emerging Markets

Different definitions have been given to the term 'emerging market' in the literature. Bekaert and Harvey (2002, p 429) state that according to the World Bank (WB) *'a country is considered 'emerging' if its per capita GDP falls below a certain level which changes through time. The basic idea behind the term is that these countries 'emerge' from less-developed status and join the group of developed countries'*. Table 2.1 below shows the WB classification of countries as low, middle or high income economies (developing or developed). The classification is per capita Gross Domestic Product (GDP) in US dollars. Recall that the per capita GDP is a country's national output (GDP) divided by the population and expressed in US dollars per person.

Table 2-1 World Bank Classifications

Classification	GDP per capita (in USD)
Low	< 755
Lower Middle	755 < 2995
Upper Middle	2995 < 9265
High	>= 9265

Source: Word Bank, 2008

It should be noted that per capita GDP is a rough measure of a country's income per person, that is, its potential for development, especially if the incomes are more equitably distributed. As a result of this potential, most high GDP countries are developed countries with equally developed markets for example the US, Japan, and European countries. However, a country may have a high per capita GDP but relatively underdeveloped stock market (sometimes such a market may not have been established in the country). Similarly, a lower income country may have a more developed (emerging) market than a high income country. Moreover, some theories of development would suggest the concept of 'catch up' potential whereby a low or high GDP country with a relatively undeveloped stock market may have a higher potential for development than one with a more developed stock market.

In other words, the effectiveness of per capital GDP as a measure of development potential of a country depends on the nature of income distribution in the country, and the extent of development of the political economy for examples the financial markets and infrastructure, which determine the country's 'catch up' potential.

For example, the per capita GDPs of Equatorial Guinea (without a stock market), Libya (about 3 years old stock market), South Africa, Egypt and Nigeria are, respectively, USD 14,941, 14,479, 5,685, 2,162 and 1,401 according to the World Economic Outlook Database for April 2011. But the last three countries are three of the four largest financial markets in Africa (including Algeria).

This shows that the state of development of a stock market and its classification as emerging or developed depends on other characteristics mentioned below. Following Hoskisson et al (2000), Nakata and Sivakumar (1997), Fuss (2002), emerging markets are described as follows: low income, rapid growth countries undergoing economic liberalization and achieving healthy economic advancement (for example, Brazil, India and South Africa, also Nigeria, as we shall see shortly); and countries which are (may be emerging from controlled to capitalist economies) and restructuring their economies along market-oriented lines for example Russia and China.

Also, following Islam and Watanapalachaikul (2005), Bekaert and Harvey (2002), Kohers (2005 and 2006), Hassan et al (2003), Fuss (2002) and Morck et al (2000), we summarise the characteristics of emerging markets thus:

- Investment returns are *not normally* distributed; they are *typically skewed* and have *fat tails*
- Compared with developed markets, emerging markets have a high degree of country risk (including political risk, economic risk and financial risk) linked to currency devaluations, failed economic plans, financial shocks and capital market reforms
- With regards to *portfolio diversification*, it seems promising to include financial assets in emerging markets into stock portfolios, since their very low correlations with well-developed markets reduces overall portfolio risk
- The markets are characterized by thin trading, low liquidity, less informed traders or traders with *incomplete* or *unreliable information*. The markets are therefore relatively shallow, not deep enough to enable them be as efficient as developed markets.

2.3 Characteristics of African Stock Markets

Similarly to the notes above for emerging markets in general, the characteristics of African markets as discussed by United Nations Economic Commission for Africa (UNECA) (2007), Yartey and Adjasi (2007), Chukwuogor (2008), Moss et al (2007), Chinzara (2008), and Ezepue and Solarin (2008), can be summarised as follow:

- 'African markets are small, with few listed companies and low market capitalization; Egypt, Nigeria, South African and Zimbabwe are the exceptions with listed companies of 792, 207, 403 and 79, respectively
- African stock markets suffer from *low liquidity*; that notwithstanding, the stock markets continue to perform remarkably well in terms of return on investment. Liquidity as measured by turnover ratio is as low as 0.02 percent in Swaziland compared with about 29 percent in Mexico. Low liquidity implies that it will be harder to support a local market with its own trading system, market analysis, brokers and the like, because the business volume would simply be too low. The NSM has almost outgrown such problems.
- The markets are not yet well integrated with regional and global markets as the emerging markets of Brazil, Russia, India and China (BRIC) countries, and have a range of capacity and technology constraints; interestingly, the Nigerian Stock Market is now digitalized and therefore weans itself somewhat from acute technological constraints. It should be noted that the *regional integration* of capital markets in Africa offers a solution to this situation, especially for the smaller economies. Overall, to accelerate *capital market development*, governments need to improve the capacity of all stakeholders, invest in infrastructure and promote *good governance*.
- Compared to China for example the African markets are characterized by political economies with low levels of saving and limited private capital flows, so the investment ratios in Sub-Sahara African (SSA) countries are lower than in other developing regions.
- While African markets are relatively small in comparison to developed markets of US, Europe and Japan, or even mid-sized emerging markets, they are not out of line with the global norms, given the size of their host economies'[2], Ezepue and Solarin (2008, pp. 5-6).

[2] The author is grateful to Ezepue and Solarin (2008) for permission to use the quoted text here.

How do the above characteristics of emerging markets apply to the Nigerian Stock Market (NSM)?

The above question is of interest because we argue here that the NSM is a good example of an emerging market. This characteristic will be related to the effects of the global financial crisis on the NSM, if any, and the nature of development of the stock market required to enable it to withstand such effects in future.

We note that the characteristics of emerging stock markets mentioned in Section 2.2 above directly apply to the NSM.

- Stock market returns from the NSM show that the returns are generally not normally distributed, highly skewed and highly peaked (leptokurtic), hence they have fatter tails than normal (Emenike, 2010).
- Also, Nigeria has a high degree of country risk (including political risk due election malpractices, economic risk), high currency fluctuations sometimes, financial shocks due to global financial crisis for example recent loss of market capitalisation in the NSM, and non-performing banks. The country consequently undergoes capital market reforms at the Nigerian Stock Exchange (NSE) led by the Securities and Exchange Commission (SEC).
- Finally, the NSM is characterised by thin trading, incomplete information (and high degree of information asymmetry), and is inefficient, Ezepue and Solarin (2008), Chukwuogor (2008).

In summary, the NSM is an emerging market, a view that is reiterated in the following statement *'Nigeria's recent private sector-led growth and vibrant capital markets, with potentials for investors placed it in a league of eight sub-Saharan African countries (outside South Africa) heading towards emerging market status'*, IMF (2008), quoted by Aledare et al (2008, p. 2).

This feature of the market has important implications for development of the NSM which we examine later in the chapter.

2.4 Background Information on the Nigerian Financial System and the Nigerian Stock Market (NSM)

In this section we describe the structure of the Nigerian financial system which includes the NSM, the characteristics of the NSM and recent developments and reforms.

2.4.1 The Nigerian Financial System Structure

As shown in Figure 2.1 below, the Nigerian Financial System comprises four main groups of financial institutions namely Insurance, Banking, Pension Funds Management and Capital Markets. The NSM belongs to the Capital Markets. The figure shows the different types of financial institutions which belong to the four groups. For examples, the banking system includes different types of banks – commercial banks, merchant banks, specialized financial institutions, discount houses, development banks, finance companies, primary mortgage institutions (PMIs).

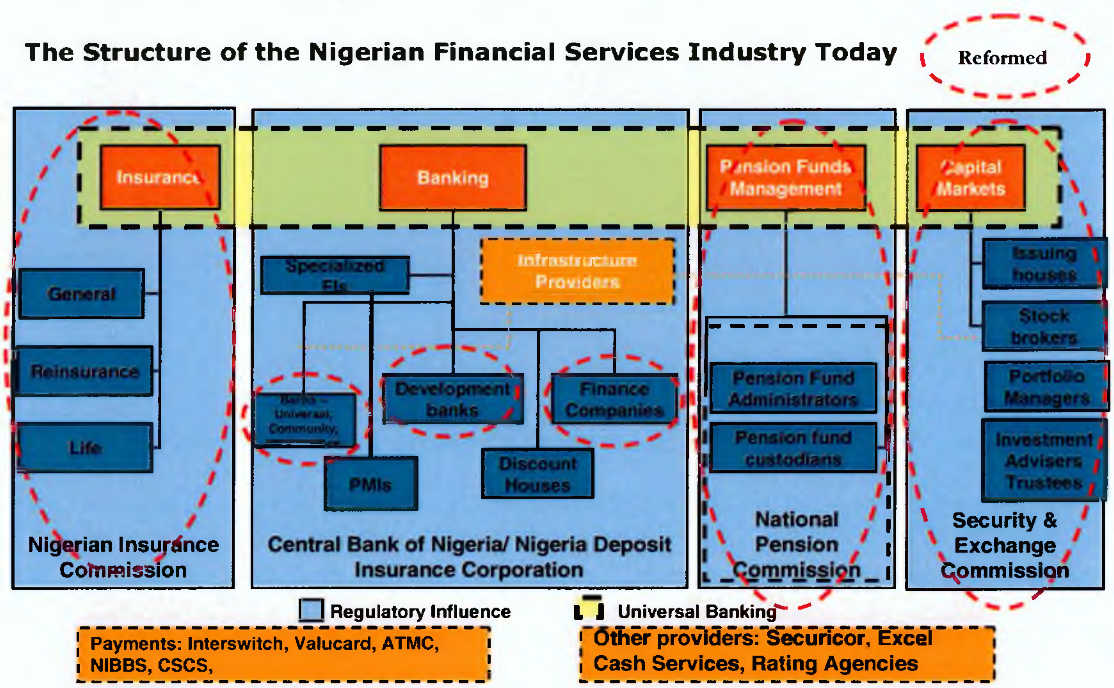

Figure 2-1 shows the structure of the financial institutions in Nigeria
Adopted from: CBN official site 2009

The four main groups of financial institutions are regulated by four institutional organisations listed at the bottom row of the figure, namely the Nigerian Insurance Commission, Central Bank of Nigeria/Nigeria Deposit Insurance Corporation, National Pensions Commission, and Security and Exchange Commission (SEC). For example, the SEC regulates the NSM through the Nigerian Stock Exchange (NSE).

The figure shows that majority of Nigerian banks are universal banks which engage in financial transactions across the four groups of financial institutions. For instance, a typical commercial bank in Nigeria, say, Zenith Bank has business lines in insurance, banking, pension funds management and capital markets.

As shown by the oval shaped broken lines indicating reforms in the financial system in Figure 2.1, virtually all parts of the Nigerian financial system have undergone reforms in the past few decades. Key aspects of these reforms are summarised later in this chapter. The results of this study will compare the behaviour of the NSM before and after the most recent financial reforms introduced by the CBN in 2004.

The Capital Markets including the NSM are very important to the financial system because all the institutions participate in the markets in order to grow their wealth. That is, insurance companies, banks, pension funds and government departments invest their funds in the capital markets and raise investment capital from the markets through share dealings. The Capital Markets are maintained by the activities of key market participants such as issuing houses, stock brokers, portfolio managers and investment advisors and trustees. Since the NSM is a dominant part of the capital markets, the performance characteristics of the NSM are vital to the overall health and economic development of the Nigerian financial system. This further explains the importance of this research on the characteristics of the NSM.

2.4.1.1 Brief descriptions of key components of the Nigerian financial system

The Federal Ministry of Finance (FMF)

The Federal Ministry of Finance advises the Federal Government on its financial operations and cooperates with Central Bank of Nigeria (CBN) on financial matters. The Federal Ministry of Finance is at the top of the financial system and all the financial organizations were under its control including CBN. The recent amendments to the laws make the CBN an independent organisation. However, recent amendment to the laws of the CBN also compels the CBN to report to the Presidency through the Federal Ministry of Finance, Bernard (2006)

The Banking Sector

With 25 universal banks providing elaborate commercial and investment banking services and over 700 community banks providing minimum commercial banking services to local communities, the banking sector in Nigeria is the strongest and most structured financial sector, Becker et al, (2008).

The Nigerian banking sector has not developed to its full potential. Nigeria remains a cash economy: the total amount of loans outstanding to the private sector is only 15.2% of GDP (2005), comparable to other Sub-Saharan economies (15% Ghana, 14% Cote d'Ivoire, 17% Benin) as shown in Figure 2.2 below. These amounts are significantly lower than those in developed economies where private sector loans are several times bigger than the GDP (261% South Africa, 300%+ UK in year 2007).

However, the Nigerian banking sector has been growing extremely fast over the past 5 years: 23% CAGR of assets, 36% CAGR of deposits, and 10% CAGR of branches. This strong growth is the product of the trust created by the transformation of the industry both with investors and clients, Becker et. al (2008).

It has been reported that the Nigerian banking system is the fastest growing banking system in Africa. By the end of 2007, about 6-7 banks had more than $1 billion in Tier-1 capital[3]; and about 10 had $2 -4 billion in market capitalization (CBN official site 2009).

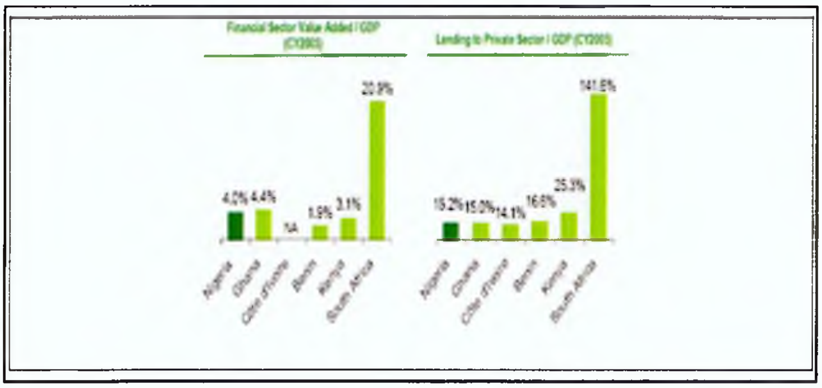

Figure 2-2 selected International Comparisons
Source: Adopted from: Becker et al 2008

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[3] **Tier 1 core capital** (or common equity as it is formally called by the Bank for International Settlements) measures a bank's equity position relative to its assets. It essentially asks how strong is the foundation on which the bank's wealth is built? Eligible capital includes common equity and declared reserves, minus certain classes of preferred shares, goodwill and hybrid capital. This is then divided by the total for risk-weighted assets. For more information see
http://www.fsa.gov.uk/pubs/cp/cp155.pdf
http://seekingalpha.com/article/311739-tier-1-core-capital-ratio-of-21-developed-market-banks

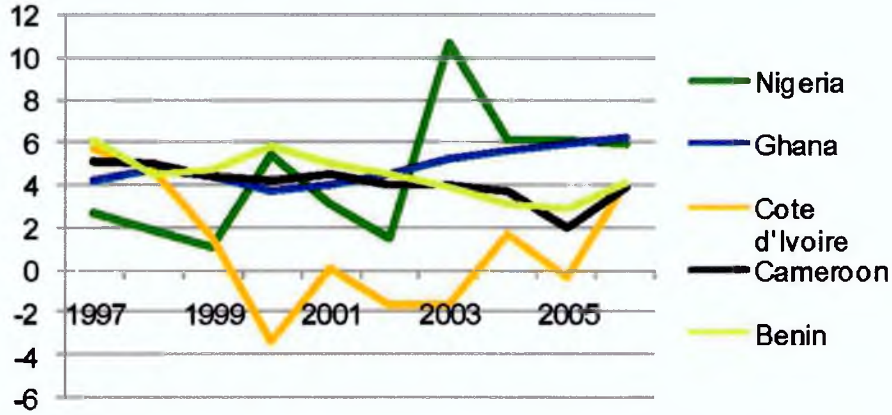

Figure 2-3 : Nigerian Economic Growth vs. Neighbours
Adopted from: CBN official site 2009

Figure 2.3 also shows that the variation in the growth profile of the Nigerian financial economy over the period 1997-2004 was more vigorous compared to its neighbours for example Ghana. The growth pattern is also more volatile than other countries.

The Central Bank of Nigeria (CBN)

The CBN is the apex regulatory authority of the Nigerian financial system. It was established by the Central Bank act of 1958 and commenced operations on 1st July 1959. Among its primary functions, the Bank promotes monetary stability and sound financial system and acts as banker and financial advisor to the federal Government, as well as banker of last resort to the bank. The bank also encourages the growth and development of financial institutions. Enabling laws made in 1991 gave the Bank more flexibility in regulating and overseeing the banking sector and licensing finance companies which hitherto operated outside any regulatory framework.[4]

The Commercial Banks

The first commercial bank was established in Nigeria in 1892. Commercial banks perform three major functions, namely, acceptance of deposits, granting of loans and the operation of the payment and settlement mechanism. Since the government commenced active deregulation of the economy in September 1986, the commercial banking sector has continued to witness rapid growth, especially in terms of the number of institutions and product innovations in the market, International Organization for Migration (IOM) (2007).

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[4] Embassy of the Federal Republic of Nigeria, Moscow, Russian Federation http://www.nigerianembassy.ru/Business/banking&finance.htm visited on 23.2.2009

The number of commercial banks and their branches rose, respectively, from 30 and 2,397 in 1986 to 64 and 2,402 in 1996. Many branches were closed down in structural rationalisation. The minimum capitalization of commercial banks has been increased to a uniform level of N500 million from N50 million. The commercial banks continue to dominate the banking sector accounting for 82.6 percent of the banking system total assets and deposit liabilities in 1996. The total assets of the commercial banks increased to N536, 057.9 million while deposit liabilities rose to N225, 298.7 million in 1996, IOM (2007).

Money and Capital Markets

As noted above, the most important components of the financial system in any country are the money and capital markets. The capital market is very important for financial system and is considered as the market for securities of long term fund and instruments such as stocks, notes and bonds, O'Sullivan and Sheffrin (2003). It improves the level of savings, provides funds for large projects and for expansion and growth. It also provides competitive alternative to the traditionally dominant commercial banking sector and improves the efficiency of investments by allocating finance to more efficient investors.

The money market is the market for short term funds (usually one year or less) and includes instruments such as treasury bills, bankers' acceptances, and commercial paper. The money market rate is usually calculated as in Equation 2.1, Islam and Watanapalachaikul (2005):

$$mr_t = \left(\frac{d_t}{1-(d_t/365)}\right)\left(\frac{365}{M}\right) \qquad \text{Equation 2-1}$$

where, mr_t is the money market rate, d is the discount and M is the days to maturity.

As mentioned above, the Securities and Exchange Commission (SEC) regulates the Nigerian capital market which is centred on one stock exchange, the Nigerian Stock Exchange (NSE). The NSE was established in 1960 with a total of 19 securities listed for trading with valued at N80 million; there were 289 listed securities, with a stock market capitalisation of some USD 46bn as at January 2007. The market has grown phenomenally over last 8 years, AFDB[5] report (2007).

[5] African Development Bank (AFDB)

There is now a great deal of international interest, and indeed participation, in the Nigerian financial system, from investments in stocks and treasury bonds to private equity investments. This trend is expected to continue as economic and political fundamentals, such as reduced inflation, improving growth rates, fiscal accountability, and transparency, are expected to be maintained, AFDB (2008)

As a result of the pension reform in 2004, income assets under management in the Nigerian Stock Exchange (NSE) have increased to N500bn ($4bn) as of April 2007. Total market capitalization of NSE grew from $16bn in 2004 to $73bn in 2007 ((Compound Annual Growth Rate (CAGR) of 66%))[6], and to over $100bn as of April, 2008 (Becker, 2008). The growth of NSE market capitalization in ($BN) and Market capitalization as % of GDP are shown in Figure 2.3.

Source: Economic Intelligence Unit, "Nigeria Country Finance 2007", July 2007.

Figure 2-4 The growth of NSM cap. ($BN) and Market cap. as % of GDP
Source: Adopted from Becker et. al. 2008

Hence, the NSE has shown vigorous growth in assets under management as well as total market capitalisation as is characteristic of emerging markets.

Foreign Exchange Market

The existence of an efficient foreign exchange market is a major element in the development of a country financial system. It would attract foreign banks and investors to investor in the market, Isalm and Watanapalachaikul (2005). The official foreign exchange market in Nigeria is currently two tiered and consists of two windows namely the Central Bank of Nigeria (CBN) and interbank windows. The CBN window is a managed float via a bi-weekly Wholesale Dutch Auction System (WDAS), where foreign exchange is sold directly to authorized dealers. The WDAS replaced the Dutch

[6] The CAGR is obtained from the relation: $1 + CAGR = \sqrt[n]{A_n / A_0}$, where the quantities under bracket are amounts at the nth and starting years, respectively. For example for the 3 years between 2004 and 2007, $A_3 = £73bn, A_0 = £16bn.$

Auction System in early 2006 in an attempt to bridge the gap between the official rate and the rate of the illegal parallel foreign exchange market that existed. The interbank market is driven by market demand and supply, but usually anchors off the CBN, AFDB official site (2008).

According to Becker et al (2008), the Nigerian foreign exchange market has witnessed tremendous changes. The Second-tier Foreign Exchange Market (SFEM) was introduced in September, 1986, the unified official market in 1987, the autonomous Foreign Exchange Market (AFEM) in 1995, and the Inter-bank Foreign Exchange Market (IFEM) in 1999. Bureaux de Change were licensed in 1989 to accord access to small users of foreign exchange and enlarge the officially recognised foreign exchange market. Exchange rates in the Bureaux de Change are market determined.

The real exchange rate data in Figure 2.4 below shows that Nigeria's naira has slowly appreciated against the dollar over the past 10 years, while the inflation rate fluctuates between 5% and 20%. Clearly, the exchange rate performance is generally good over the period, but the inflation rate in the system is generally lower in the 1997-2000, higher in 2001-2005 and begins to drop to the pre-reform values from 2005, probably as a result of the reforms.

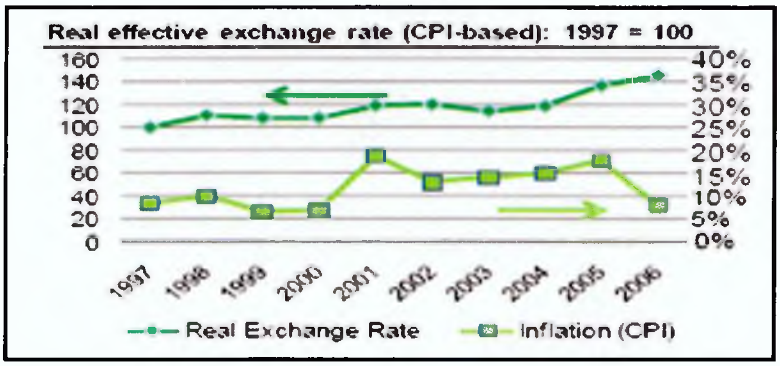

Figure 2-5 Average exchange rate, Nigerian naira per US dollar, 1997- 2006
Source: adopted from Becker et al (2008)

Insurance Sector

The insurance services existed in Nigeria since 1920's, mainly offered by British companies. In the 1970's and 80's a process of indigenization occurred when most of the foreign insurance companies withdrew from the market and new local entrepreneurs launched insurance firms.

As part of the financial reforms in the system, the National Insurance Commission raised the minimum capital requirement for insurance companies from N150m ($1.1m) to N2bn ($15m) for life, from N200m ($105m) to N3bn ($22.6m) for non-life, and from N350m ($2.6m) to N10bn ($75m) for reinsurance companies. As a result, insurance firms consolidated; the number of the insurance firms decreased from 118 in December 2002 to 71 in March 2007, Becker et al (2008).

After the reforms in 2004, insurance market size has been increasing gradually. The total gross premium of insurance companies has grown from $221m in 2000 to $716m in 2006 (CAGR of 22%). However, insurance penetration is still very low. The market size for the sector is only 0.5% of GDP whereas the market size in South Africa is 16% of GDP[7].

2.4.2 Nigerian Stock Market: General Characteristics

Stock market development can be characterized using three main characteristics: traditional, institutional and asset pricing, Demirgüç-Kunt and Levine (2004). Traditional characteristics are concerned with basic growth measures of stock market. These measures include number of listed companies and market capitalization. The institutional characteristics are the regulatory and legal roles that may influence functioning of the market, information disclosure and transparency requirements as well as market barriers and trading costs. Lastly, the asset pricing characteristics focus on the efficiency of the market especially in relation to the pricing of risk, Becker et al (2008). These market efficiency characteristics of the NSM are discussed in Chapter 6 of this thesis. We focus on the first two characteristics in this section.

Traditional Characteristics

a) Market Size

As it is seen in Figure 2.6 and Table 2.2, from 1985 the number of securities listed in the NSM has increased from 96 to 223 in June 2008 with increase of trading volume from 17.2m to 120,757.30M in the same period. Figure 2.6 shows that this development has been started from 1989 and reached 214 in 2005 a year after Prof Soludo the governor of CBN had launched his reforms' in Nigerian financial System. Also as

[7] Report on Nigeria financial services cluster analysis and recommendations Submitted for: Professor Michael E. Porter: The Microeconomics of Competitiveness: Firms, Clusters & Economic Development May 2nd, 2008. Available at http://www.isc.hbs.edu/pdf/Student_Projects/Nigeria_Financial_Services_2008.pdf

mentioned above the total market capitalization in column 5 of Table 2.2 (converted to US dollars) grew from $16bn in 2004 to $73bn in 2007 (CAGR of 66%), and to over $100bn as of April, 2008. Therefore, in terms of market size, the NSM shows evidence of high growth.

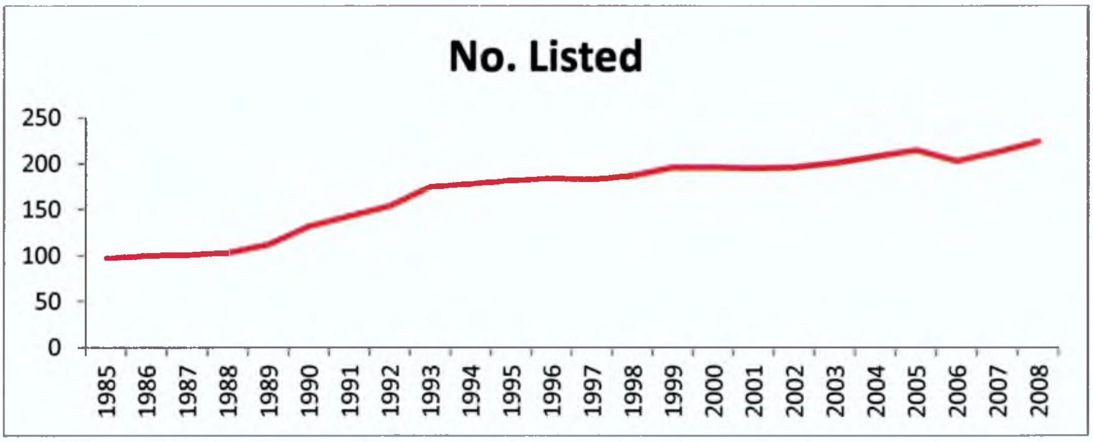

Figure 2-6 Number of securities listed on The Nigerian Stock Exchange

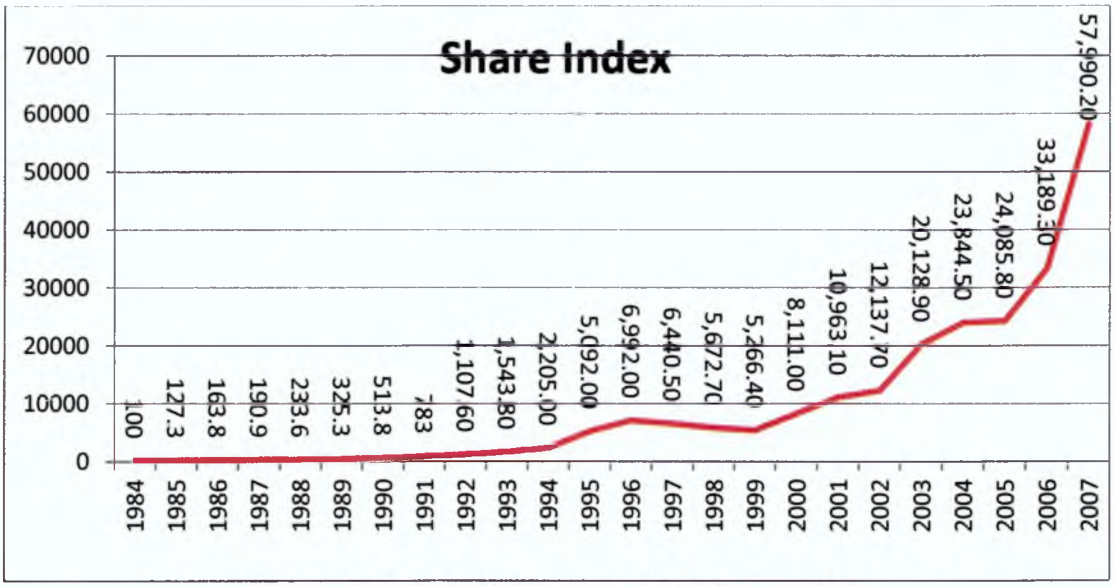

Figure 2-7: Plot of Nigerians' All share index

Adopted from: NSE official site 2009

The plot in figure 2.7 shows on average an exponential growth in the all share index, which is evidence of a very dynamic stock market in the period 1984-2007. It should be noted that this comment on exponential behaviour of the share index refers to the indicated period, since following the global financial crisis, the stock market behaviour changed, as mentioned in Chapter 9 of the thesis.

Remarks

We note that the figures in the figure are nominal instead of real values and therefore do not give the most accurate picture of the relative sizes of the index from year to real terms since the figures are not adjusted for, say, differences in inflation rates, consumer price indexes, etc. That said, the figures still show a fairly exponential growth in the All Shares Index over the years.

b) Liquidity

Basically, liquidity refers to the ease with which an asset (in this case securities) can be turned into cash through an efficient market. That is, the ability to easily buy and sell securities. Demirgüç-Kunt and Levine (2004) identify two main reasons why liquidity is important in the characterization of stock market.

Table 2-2 Performance of Equities Listed on the Nigerian Stock Exchange

Year	No. Listed	Trading Volume (m)	Trading Value (=N='m)	Mkt Capt. (=N='m)	Stock Index	Change in index %	Turnover Ratio %	Average P/E Ratio	Average Div. Yield %
1986	99	19.2	22	3,687.80	163.8	28.7	0.6	3.8	9.9
1987	100	23.5	27.2	4,031.60	190.9	16.5	0.7	4.7	11.2
1988	102	18.8	22.4	5,089.00	233.6	22.4	0.4	4.8	10.7
1989	111	19.5	22.9	8,034.70	325.3	39.5	0.3	5.6	11.7
1990	131	52.6	87.8	12,134.80	513.8	57.9	0.7	7	12
1991	142	47.2	90	18,447.50	783	52.4	0.5	5.7	10.4
1992	153	105.7	237.1	26,245.80	1,107.60	41.5	0.9	6.8	7
1993	174	186.7	286.6	41,830.90	1,543.80	39.4	0.7	6	6.5
1994	177	190.8	401.3	61,023.90	2,205.00	42.8	0.7	6	8.4
1995	181	346.1	1,788.10	175,064.70	5,092.10	130.9	1	6.8	7.9
1996	183	733.5	6,922.60	279,783.20	6,992.10	37.3	2.5	10.5	9.6
1997	182	1,160.00	10,923.20	276,304.60	6,440.50	-7.9	3.9	10.7	8.7
1998	186	2,080.60	13,555.30	256,774.70	5,672.70	-11.9	5.1	8.2	6.6
1999	195	3,913.60	14,026.60	294,465.30	5,266.40	-7.2	4.8	5.6	7.8
2000	195	4,998.10	28,154.60	466,058.70	8,111.00	54	6	7.1	7.5
2001	194	5,890.80	57,612.60	648,449.50	10,963.10	35.2	8.9	9.7	7.3
2002	195	6,615.90	59,311.30	748,734.60	12,137.70	10.7	7.9	6.8	10.8
2003	200	13,242.10	113,886.60	1,325,672.90	20,128.90	65.8	8.6	8.6	10.5
2004	207	18,982.10	233,885.60	1,926,465.10	23,844.50	18.5	11.6	9.5	9.7
2005	214	26,493.70	254,707.80	2,523,493.30	24,085.80	1	10.1	12.8	9.5
2006	202	36,661.20	468,588.40	4,228,572.10	33,189.30	37.8	11.1	9.2	10.6
2007	212	138,070.00	2,083,339.00	10,301,000.00	57,990.20	74.7	20.2	5.3	15.7
2008	223	120,757.30	1,723,339.80	10,923,629.20	55,949.00	-3.5	15.8	28.7	4.3

*2008 provisional (Jan -Jun)

Source: Nigerian Data Bank (2008)

The first reason is that liquidity relates to the riskiness of an investment. An investment is deemed to be less risky where investors are able to alter their portfolios quickly and cheaply. The second is that in a liquid market allocation of capital is more efficient which enhances long-term economic growth, Osinubi (2004).

There are two main measures of liquidity namely total value traded ratio and turnover ratio.

a) Total value traded ratio is the total value of shares traded on the Stock market exchange divided by GDP. It measures trading of equities as a share of national output, it measures liquidity on an economy wide basis. The NSM has an average of 0.25 per annum for the study period (not stated in the table).
b) Turnover ratio is the value of total shares divided by capitalization. High turnover reflects low transaction costs. Table 2.2 shows that the turnover ratio grows from a value of 0.5% in 1985 to 20.2% in 2007 (a period of 22 years equivalent to a CAGR of 18%). Using two years before and after the 2004 financial reforms as examples, the CAGR values for 2001-2003 (pre-reform period) and 2005-2007 (post-reform period) are 24% and 41%, respectively. Hence, while the liquidity as measured by the turnover ratio grows vigorously at 18% over the entire period, the rate of growth in the post-reform period is nearly double that in the pre-reform period. Thus, the increased capitalisation of banks and other financial institutions as a result of the reforms appear to have increased the liquidity of the NSM.

Institutional Characteristics

a) Regulatory Institutions

Regulation is seen as a way of buoying up investor's confidence in brokers and other capital intermediaries and stakeholders. It ensures fair play and transparency in the market operations. This in turn encourages investment and trading in the stock market.
Nigerian capital market had from the onset ensured that a strong institutional framework was in place through the establishment of Capital Issue Commission (though with no legal status), which later metamorphosed to Nigeria Securities and Exchange Commission in 1979 and serves as the apex regulatory body of Nigerian capital market. Of added importance is that the Nigerian Stock Exchange itself is a self-regulatory institution[8].

[8] see (Akamiokhor, 1984; Inanga and Emenuga, 1997)

b) Transaction costs

One of the relative measures of the efficiency of a stock market is the level of transaction cost. The higher the transaction cost the more likely that the market will become highly inefficient since investment in some asset classes with such costs will be restricted to market participants who can afford them, thereby distorting the allocation of capital to possibly more valuable investment opportunities. Transaction costs can either be viewed from the perspective of an investor or that of the companies. From a company's point of view, transaction costs include all expenses incurred in the bid to make public offer of equity or loan stock. For an investor, transaction costs include all expenses incurred in the purchase of shares or loan stock. Identifiable transaction costs in the Nigerian capital market include: application fee (0.5%), valuation fee (0.75%), brokerage fee (1%) and vending fee (1%). Other costs are payment to auditors, solicitors, advertising and administrative expenses, Inanga and Emenuga (1997).

c) Openness and market barriers

Until 1972 when the Indigenisation Decree was promulgated, there was no restriction to foreign investors in the Nigerian capital market. The Decree also known as Nigerian Investment Promotion Decree was amended in 1977 and it effectively restricts capital inflows to a maximum of 40% equity holding in listed security among other stringent measures. The Decree was again amended in 1989 during the privatization era. This time it was aimed at encouraging domestic investment by foreigners. However, total deregulation of the capital market was helped by the Nigerian Investment Promotion Commission Act of 1995, Foreign Exchange (Miscellaneous Provisions) Act of 1995 and recently the Investment and Securities Act of 1999. Foreigners now participate in the Nigerian capital market both as operators and investors. There is no limit any more to the percentage of foreign holding in any company registered in Nigeria.

As at 2000, foreign holdings on the Nigeria stock exchange is 3.96% on the average, BGL Financial Monitor, (2001). This figure is still very low and needs to be improved by proactive intervention in the NSM and Nigerian financial markets, especially in the context of financial reforms and market regulations which strengthen the confidence of foreign investors to invest in the country, Balogun (2007).

2.5 Recent Developments and Reforms in the Nigerian Financial System

During the year 2004, the Federal Government launched the National Economic Empowerment and Development Strategy (NEEDS), a medium term economic reform agenda, with the primary objectives of poverty reduction, wealth creation and employment generation. Also, the programme accords high priority to the private sector as the engine of growth through which an estimated seven million new jobs would be created (Nigerian Stock Exchange website, 2008). The economic performance was mixed with significant gaps between expectation and achievement, despite stellar performances in the telecommunications sector and the management of the foreign exchange rate, Balogun (2007). General economic growth was constrained by a resurgent inflationary pressure, high lending rate, the inability of the refineries to work at full capacity, and weak infrastructure support, especially epileptic power supply and dilapidated intra-city road network (Nigerian Stock Exchange website 2008), Balogun (2007), Sanusi (2011), Olaleye (2011).

To strengthen the financial sector and improve availability of domestic credit to the private sector, a bank consolidation exercise was launched in mid-2004 when the then new CBN Governor, Professor Soludo, launched the reforms. As a part of the reforms the CBN requested all deposit banks to raise their minimum capital base from about US$15 million to US$200 million by the end of 2005, Becker et. al (2008), Balogun (2007).

The Nigerian financial system has experienced some remarkable changes in recent times.

Some of these developments include:

- The promulgation of the unsuccessful Banks (Debt Recovery) and financial mismanagement in Banks Decree No.18 of 1994. This is to ease the prosecution of those who contributed to the bank failures and to recover the debt owed to the failed banks.
- The launch of Financial Services Regulatory Coordinating Committee (FSRCC) by the CBN in 1994. The aim was to organize and regulate the regulatory policies of all financial institutions in the system with a view to developing coherence and comprehensiveness.

- The CBN also granted forbearance to finance firms operating in Nigeria whereby they were granted a maximum of four years to pay back their classified assets portfolio against their present profits. The minimum borrowing of the finance firms had been reviewed downward from N100,000.00 to N50,000.00 since 1994.
- Three essential decrees for further clarification have been implemented in the financial system in 1995; they were the Money Laundering Decree, the Nigerian Investment Promotion Commission Decree and the Foreign Exchange (Monitoring and Miscellaneous Provisions) Decree.
- The Money Laundering Decree aims to stop illegally acquired assets from entering the Nigerian financial system such as drug money in order to prevent the harmful effects of such money. The Decree confines the maximum amount of cash payments that can be made or accepted to N500,000 for an individual and N2 million for corporate bodies. Any amount in excess of these limits is to be reported to appropriate authorities.
- The Nigerian Investment Promotion Commission is charged with stimulating, improving and coordinating investment activities in Nigeria. The Commission is empowered to start and sustain measures which would encourage the investment environment in Nigeria for both indigenous and foreign investors. The Commission is also empowered to list any enterprises in which foreign contribution is allowed and to permit foreign enterprises to purchase shares of any Nigerian enterprises in any convertible foreign currency.
- The Foreign Exchange Decree recognized an autonomous foreign exchange market. The Decree empowers the Central Bank of Nigeria, with the approval of the Finance Minister, to issue strategy to control the measures for transactions in the market as well as other actions which may boost the effective operation of the market. The decree provides for any convertible foreign currency to be traded in the market. It also permits individuals whether living in or outside Nigeria to invest in Nigeria.
- In 1997, the CBN Decree 24 and BOFI Decree 25 both of 1991 were modified. The highlights of the modification include the withdrawal of the autonomy of the CBN with its supervision placed under the Federal Ministry of Finance. Nevertheless, the Bank powers over the institutions within the financial system were enhanced. All financial organisations are under its supervision, including the Development Financial Institutions.

- A new insurance decree was also passed which stipulates new capital needs for insurance firms and also created the National Insurance Commission as the regulatory body in the industry.
- The trading system was introduced and computerised in the Nigeria Stock Exchange to help trading on the floor of the Exchange and stimulate processing and settlement of transactions and ease the internationalization of the Exchange.
- The Nigeria Deposit Insurance Corporation Decree 22 of 1988 was modified to provide more powers to the Corporation to deal with insured banks and to take action independent of the CBN on some matters influencing problem banks.
- With particular reference to the banking system, it is crucial to comment on the antecedents to the reforms in this sector. As at the end of June 2004, there were 89 banks with many banks having capital base of less than USD10million, and about 3,300 branches. Structurally, the sector is highly focused as the ten largest banks account for about 50 percent of the industry's sum assets/liabilities. Even the largest Bank in Nigeria has a capital base of about US$240 million compared to US$526 million for the smallest bank in Malaysia. The relatively thin capital base of the banks, each with costly headquarters, separate investment in software and hardware, heavy fixed costs and operating expenses, and with bunching of branches in the commercial centres led to very high average cost for the industry. This increases intermediation costs, broadens the difference between deposit and lending rate, and puts extra pressure on banks to engage in sharp practices as ways of survival, Ebong (2006).

Most of the banks did not encourage savings, but were just traders. Depositors with balances of less than N50,000 to N100,000 are not welcome. The preference was toward high net-worth agents for deposits such as government agencies, blue chip companies and wealthy individuals. Without prejudice to the existence of a enormous informal economy, this alienation of small depositors could be blamed for the existence of over N400 billion outside the banking system as at 2004. Also real sector operations in agriculture and manufacturing were neglected. This condition is neither sustainable nor healthy for the economy.

As at the end of March 2004, the CBN's ratings of all banks categorised 62 as sound/satisfactory, 14 as marginal and 11 as unsound, while two of the banks did not make returns during the period. The essential problems of the banks, particularly those categorised unsound have been known to include: persistent illiquidity, poor assets quality and unbeneficial operations. In general, the major concerns with many Nigerian banks include:

- Imprecise reporting and non-compliance with regulatory condition, unhealthy competition and falling ethics
- Late or non-publication of annual accounts which weakens market discipline in ensuring the soundness of banks
- Total insider abuses, resulting in enormous non-performing insider related credits
- Bankruptcy, as proven by negative capital sufficiency ratios and shareholder's funds that had been totally eroded by processing losses
- Weak capital base including the banks that have met the minimum capital needs of N1 billion as of 2004.
- Over-dependence on public sector deposits and abandoning other classes of savers.

Further notes on bank restructuring and the global financial crisis

In order to further contextualise this research, we present the following key ideas in the literature on Nigerian financial system.

Balogun (2007) provides interesting perspectives on the Soludo banking sector reforms as follows. The broad objectives of the reforms include:

- Less intervention in the market with the view to promote a more efficient resource allocation
- Expanding the savings mobilization base in support of investment and growth through market-based interest rates
- Improving the regulatory framework and procedures in order to forestall bank distress
- Fostering competition in banking services
- Laying the foundations for minimal inflationary growth and enabling environment for economic development.

Balogun (2007) also notes that the policy instruments often used to achieve these objectives include:

- Foreign exchange market and interest rates deregulation

- Adoption of market based approach to credit allocation
- Pursuit of sustainable fiscal and monetary policies
- Reforms or restructuring of financial markets via legislative changes
- Active use of prudential regulations and capital adequacy requirements.

Typically, the extent of reforms is guided by the severity of distortions in the financial system and markets and the negative impact of the disincentives created by the distortions especially for key economic development goals such as private sector-led growth and low unemployment.

Further ideas explored in Balogun (2007) in relation to the 2004 bank restructuring exercise include:

- improving the efficiency of the financial system and ensuring that proportionate to the high profit levels they were making, the banks sufficiently catalyse economic development by lending to the real sectors of the economy;
- deepening the financial markets and reducing their dependence on public sector and foreign exchange trading;
- harmonising fiscal and monetary policies to remove inherent contradictions in the policy bases which distort market signals in the financial markets;
- improving the ability of Nigerian banks and financial organisations to compete in the global financial markets;
- ensuring a healthier balance among sectors of the financial system whereby other sectors for example agriculture and mining contribute higher shares of the GDP;
- achieving effective interest rate restructuring, macroeconomic stabilization via monetary control policies, and exchange rate stabilization;
- using effective monetary and fiscal policies to reduce precautionary and speculative demand for money, hence speculative bubbles in the NSM; and
- getting market prices right in order to reduce conflicts in the twin objectives of attaining a good balance between foreign and local investments in the Nigerian financial markets including the NSM.

In Sanusi (2011), the CBN Governor who replaced Professor Soludo notes further as follows:

- Despite the lack of clarity between sharp and moderate price swings or between normal financial pressure and severe financial crisis, the crisis can be in the form of a banking crisis, speculative bubbles, international financial crisis, and economic crisis.

- While the Securities and Exchange Commission (SEC) is the apex regulatory agency for the Nigerian capital market, the Nigerian Stock Exchange (NSE) has oversight function on the professional activities of its members for example stockbrokers and is required to provide periodic reports to the SEC.
- The Nigerian capital market enables organisations to raise funds through Initial Public Offerings (IPOs) in the primary markets and trading of securities in the secondary markets. As a major source of appropriate long-term funds, the capital market is vital to Nigeria's economic development since it mobilises savings from different economic units such as governments, households, and firms for borrowing by any of these market participants, and improves the efficiency of capital allocation through competitive pricing mechanisms.
- In order to fulfil its developmental role in the market, the SEC has embarked on some of the above-mentioned reforms for example enhancement of its regulatory oversight (indeed, the SEC removed the former Director-General of the NSE, Professor Ndidi Onyiuke-Okereke to facilitate these changes), and protecting investors from market malpractices through sound registration, surveillance, investigation, enforcement, and rule-making of/for market players.
- Even though the Nigerian economy was initially perceived to have been unaffected by the 2007 global financial crisis as a result of its very low exposure to the global financial market (1.81% of investment capital as at 2009), the effects became evident by March-end 2008 with the crash in the capital market and contagion effect associated with international financial links between some banks and foreign banks who had to repatriate funds invested in these banks. These withdrawals of portfolio holdings, given the size of the Nigerian market, led to significant volatility in the market and sharp decline in stock prices across the NSM.

Similar to the above notes from Balogun (2007), the CBN blueprint for reforming the Nigerian financial system include:

- four pillars – enhancing the quality of banks, establishing financial stability, enabling healthy financial system evolution, and ensuring that the sector contributes to the real economy;
- an internal transformation of the CBN (institutional reforms);

- instituting hybrid monetary policy, macro-prudential rules, directional economic policy, and counter-cyclical fiscal policies;
- further development of capital market as alternative to bank funding;
- ensuring that banks are not universal but specialise into international, national, regional, and monocline, and Islamic operations, with different capital requirements in line with the depth of their activities; and
- creation of the Asset Management Company of Nigeria (AMCON) with a mandate to soak up toxic assets of the CBN-rescued banks and provide liquidity to them as well as assist in their capitalization.

Sanusi (2011) also notes the following capital market reforms by SEC which compliment the bank sector reforms and form a backdrop to the policy implications of this research:

- development of the Nigerian bond and fixed income markets such as used by pension funds, insurance companies to enable them effectively finance infrastructural and industrial development critical to Nigeria's economic development;
- addressing issues in corporate governance of entities and players in the market;
- adoption of International Financial reporting Standards (IFRS) by listed companies and regulated entities by January 2012;
- instituting a 40% downward review of transaction costs (fees and commissions charged by stockbrokers and market players);
- converting the Abuja Stock Exchange into a Securities and Commodity Exchange which commenced trading in 2006 on six selected grains (sorghum, maize, cowpea, Soya beans, sesame seeds and millets);
- enabling retail investors to more actively participate in the markets through Collective Investment Schemes (CIS), with 40 CIS mainly specialised in such asset classes as bonds, equities, balanced between equities and bonds, fixed income, money market instruments, Islamic and Real Estate Investment Trusts (REITS); and
- correspondingly reviewing and enhancing the quality of programs offered by the Nigerian Capital Markets Institute.

2.6 Some notes on the importance of oil in Nigeria's financial markets and economic growth

Given that Nigeria's economy is heavily dependent on oil revenue, we provide the following notes from Akinlo (2012) on the links among the oil industry sector, the NSM (financial markets overall) and economic development, which are vital for properly situating future research on NSM characteristics at sector and company levels. The notes include:

- the fact that the five main sectors used in Akinlo (2012) are cointegrated and oil can cause non-oil sectors to grow, the sectors involved are agriculture, manufacturing, oil, building and construction, trade and services;
- the existence of unidirectional causality from manufacturing to agriculture and trade and services, but no causality between agriculture and oil;
- the fact that Nigeria appears to suffer from the 'oil curse' effect whereby huge revenues earned from oil complicates macroeconomic management and creates net poverty;
- the possibility that volatility in the oil market introduces volatilities (significant fluctuations in asset prices) in other sectors of the economy;
- oil price-driven pro-cyclical government policy exacerbating asset price volatilities further; and
- consequently, to ensure that oil fosters better growth and development, the need to focus attention on three policy areas – sustenance of the oil sector reforms to enhance efficiency and transparency, deregulation of the oil sector to allow private initiatives and reduce corruption and rent-seeking behaviour on the part of oil industry officials, and the integration of the oil sector into the economy through increased employment and positive value added.

2.7 Summary

This chapter provides an overview of emerging (African) stock markets and shows that the Nigerian stock market has the characteristics of emerging markets. The chapter also describes in some detail the characteristics of the Nigerian financial system of which the NSM is a major part.

The discussion of the characteristics of the Nigerian financial system shows that the Nigerian capital market has experienced vigorous growth over the period 1985 to 2008, measured by different indicators such as market capitalization, number of shares traded, stock market index and liquidity measures for example turnover ratio. It is shown that the behaviour of the NSM shows higher growth in the pre-reform period than the post-reform period. Thus, since 2004 when the government had launched its significant reforms in the country's financial system the NSM has been doing very well and this can be seen from the average growth in the economy and the growth in the stock exchange.

However, although Nigeria is the second biggest market in Africa behind South Africa and bearing in mind the significant developments that have been achieved up to now in the system, the Nigerian financial system still needs more development compared with other emerging markets such as Brazil, India and China. The related reforms are summarised in line with the main ideas contained in Balogun (2007) and Sanusi (2011).

The chapter also highlights the importance of the oil sector to the Nigerian financial markets and economic development based on ideas in Akinlo (2012).

The relevance of these background notes on the Nigerian financial system for this research is that they provide a backdrop for discussing the implications of the research results for welfare economics and economic development of the country, particularly when viewed through the lenses of investments, financial reforms and policy making, and stock and capital markets development.

CHAPTER 3: LITERATURE REVIEW

3.1 Introduction:

This chapter reviews the literature underlying the research, especially as regards the key issues which summarise the behaviour of stock markets. These are market efficiency, bubbles, anomalies and volatility. The overall literature review for the research consists of the general ideas on these issues and how they relate to stock market performance, as discussed in this chapter, and more technical discussions of the models used in studying the issues in further chapters focusing on the issues.

3.2 Literature on Market Efficiency

Overview

Maurice G. Kendall was one of the pioneers of the research on market efficiency. Investigating the price movements in stocks and commodities he found that these prices do not follow any pattern; that is the prices follow a random walk and are independent of each other, Brealey and Myers (2000). Efficient markets are markets in which asset prices fully reflect the available information (Fama, 1970 cited in Brealey and Myers, 2000). There are no arbitrage opportunities in efficient markets. In other words, in efficient markets the investors cannot make abnormal gains because the available information is already accommodated in the prices. Random price movements refer to the movement in which the prices are subject to only the available information and nothing else and the future prices are as unpredictable as the future information, Lawler and Limic (2010).

Market efficiency is a critical concept for any economy. Capital markets are important source of funding for businesses since together with money markets they are drivers of an economy, Mathieson and Schinasi (2000). For instance, Hirschmann[9] (2011) argues that 'money market funds play a critical role in the U.S. economy because they work well in their current structure to serve the investment, cash management and short-term funding needs of businesses across America. Corporate treasurers rely on money market funds to efficiently and affordably manage liquidity. Money market funds provide a

[9] David T. Hirschmann is a President and Chief Executive Officer of Center for Capital Markets Competitiveness of the United States Chamber of Commerce. The statement is available at: http://www.preservemoneymarketfunds.org/wp-content/uploads/2011/12/USCC_2011_11_17_MMF_Letter_to_Schapiro_2_13226896561.pdf

liquid, stable value investment with a reasonable rate of return. More importantly, money market funds represent a major source of funding to the $1.1 trillion commercial paper market, allowing businesses to meet their daily working capital needs'.

According to Governor of Central Bank of Nigeria (2011)[10] *"the capital market is a market for raising funds by organizations and sale of securities. It is the main source of long-term funds to finance investment. Major studies have identified that viable projects have collapsed due to the mismatch of funds utilized".*

These markets act as intermediaries for distribution of capital from investors to the firms using the pricing mechanism. It is thus extremely essential that the investors have the correct information as availability of decision sensitive information allows investors to make informed decisions about allocating their capital. Because all investors do not have the skills and resources to acquire information about all possible investments, it is critical that prices correctly reflect the available information; in other words, it is critical that markets are efficient.

Inefficient markets will mean a strong possibility of mismatch between risk and returns which will ultimately defy the main principles of capital markets. Efficiency of markets ensures that investment capital is allocated more effectively so as to maximise market return investment and minimise risk, Brealey and Myers (2000). If the markets are efficient then it will not be possible for investors to identify any undervalued or stock because, there cannot be any undervalued stock, Damodaran (2002). However; in inefficient markets there is strong possibility to have both undervalued and overvalued stocks. As Jensen (1978, p. 5) noted:

"I believe there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis. That hypothesis has been tested and, with very few exceptions, found consistent with the data in a wide variety of markets. Yet we seem to be entering a stage where widely scattered and as yet incohesive evidence is arising which seems to be inconsistent with the theory."

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[10] A report on The Impact of the Global Financial Crisis on the Nigerian Capital Market and the Reforms by: Mallam Sanusi Lamido Sanusi, the Governor of Central Bank of Nigeria. Presented at the 7th Annual Pearl Awards and Public Lecture Held at the Muson Centre, Onikan, Lagos May 27, 2011, p. 3. available at:
http://www.pearlawardsng.com/uploads/downloads/the_impact_of_the_global_financial_crisis_on_the_nigerian_capital_market_and_the_reforms.pdf

Following Jensen's research, several authors started to investigate possible evidence of market inefficiency. These researches led to discovery of exceptions to the EMH; for example, Reinganum (1984) identified several anomalies such as the price earnings ratio (P/E) anomaly, the small firm effect, the January effect and others, De Bondt and Thaler (1985).

Further research into "winner and loser" portfolios further confirms that markets are not always efficient, Bulkley and Harris (1997). One recent example of market inefficiency is the current subprime crisis and previous stock market crashes such as the black Fridays (for examples October 10, 2008 and November 27, 2009 related to the Dubai market crash).

The question whether stock markets are efficient, thus, remains open to debate, Lawler and Limic (2010), and knowing to what extent a stock market such as the NSM is efficient or not determines the effectiveness of investment decisions in the market. It also helps policy makers in the NSM and SEC of Nigeria to gauge the nature of policies needed to make the market more efficient.

3.2.1 Perspectives on market efficiency

The most commonly cited definition of efficient markets was the one given by Fama. According to this definition, "Efficient markets are markets in which the prices fully reflect the available information" Fama, (1970, p383). However; Grossman (1976) contradicted this definition and argued that if the prices fully reflect the information then no investor will invest in acquiring the information. And if no investors will invest in acquiring the information then how will the information be accommodated in the prices. This is a conundrum. Grossman and Stiglitz (1980) clarified this conundrum by categorising the investors as 'informed' and 'uninformed'.

Informed investors seek information and use the acquired information to set their prices. Uninformed investors rely on the information acquired by informed investors and pay the premium to informed investors for the latter's investment in acquiring the information. Still their model could not completely explain the pricing as their model contained some unexplained noise. This means that investors can search for the information and use this information to make some gains and this also means that the prices do not always fully reflect the available information, Garde and Prat (2000). In other words, markets are not always efficient.

After Fama, Jensen (1978) also provided a definition of market efficiency and suggested that:

"A market is efficient with respect to information set φ_t, if it is impossible to make economic profits by trading on the basis of information set φ_t. Economic profits here refer to risk adjusted return net of all costs and Information set φ_t refers to the different amount of information existing in the different levels of market efficiency.", Jensen (1978, p96)

Jensen thus suggests that there are three faces of this definition: the Efficient Market Hypotheses (EMH), the theory of random walks and the rational expectations theory. Damodaran (2002) further elaborated on Jensen's definition (especially in context of investment decision making) and suggested that:

"An efficient market is one where the market price is an unbiased estimate of the true value of the investment. " Damodaran (2002, p2)

In efficient market, the price would reflect the available information hence investment decision making would involve justifying the current market price. In an inefficient market there would be some difference between true and market value and investment decisions can be made depending on the direction of the difference; for example, if the true value is less than market value of a stock then investors should not invest in the stock, but if the true value is higher than market value then investors should invest in the stock, Damodaran (2002).

Market efficiency does not mean that the prices have to be true value but only that the prices are unbiased so that the price movements are random. This concept of random walk is central to the EMH. In other words, in an efficient market any stock can be overvalued or undervalued to equal probability and there is no possibility of any stock being undervalued or overvalued with any more certainty. However, some individuals may be more knowledgeable or lucky (for example, Warren Buffet) to be able to consistently beat the market by correctly identifying undervalued stocks, Damodaran (2002).

In efficient markets, investors often refer to the term "fundamentals". Fundamentals are used to calculate the true value of a stock. However, some of the factors included in the calculations are uncertain and hence the true value of a stock using fundamentals depends on how accurate are the predicted variables. Here we must mention the cost of information. EMH will be completely true only if the cost of acquiring the information is nil. If there is a cost associated with acquisition of information then this cost will reflect in the price of the stock, Grossman and Stiglitz (1980). In real world we can assume that the stock price reflects the information up to the point where the marginal benefits equals the marginal cost of collecting the information, Barnes (2009).

Generally, market efficiency enables asset price and valuations to be estimated using random walks and mainstream financial economics models, which are consequences of rational expectations theory; these models depend on the nature of market information available.

The term efficiency refers to the efficiency of allocation in efficient markets as it indicates that efficient allocation of capital will ensure maximum return on allocated capital. Efficiency can be further categorised as:

- Pricing efficiency: this refers to the condition that the prices reflect all available information.
- Operational efficiency: It refers to minimisation of transactional and information costs.
- Allocation efficiency: This refers to allocation of capital to firms which can maximise return on this allocated capital.

However, we can also assume that there is a strong link between pricing efficiency and allocation efficiency because the former will contribute to the latter. In this thesis efficiency refers to pricing efficiency as stated under the EMH. According to Fama (1970, p. 383):

"The primary role of the capital market is allocation of ownership of the economy's capital stock. In general terms, the ideal is a market in which prices provide accurate signals for resource allocation: that is, a market in which firms can make production investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that securities prices at any time 'fully reflect' all available information".

3.2.2 Specification of the information set and forms of the EMH

Markets can be further categorised in three parts according to the manner in which information is available/utilised in the market: weak form efficiency, semi-strong form efficiency and strong form efficiency. In weak form efficiency the information set includes only historical return data. In semi strong form efficiency, the information includes in addition all publicly available information. In the strong form efficiency the information set includes also both public as well as private information which may be available to selected participants.

In weak form efficient markets, the market values follow a random walk model and none of the players can make any abnormal gains by virtue of a superior investment strategy. In weak form efficient markets pricing is often done using historical return data and some statistical modelling techniques, Brealey and Myers (2000). But returns are dependent on several other factors such as dividends and interest rates etc. Fama (1991) introduced a new stream of tests known as *tests for return predictability*, which allowed the investors to include these factors into the models.

In *semi-strong* form of efficiency participants have equal and unbiased information which means that investors cannot get abnormal returns unless they invest in acquiring unique and useful information privately. Researchers use "Fundamental analysis" to study such markets. Fundamental analysis involves analysing whether the prices fully reflect the *publicly* available information. Since this information mostly involves timely information released by the firms and investment firms etc, Fama (1991) termed these tests *event studies*.

In strong form efficient markets it is impossible to make any superior gains over the market because the information set includes both public and private information. Thus, strong form efficiency tests include testing for the *private* information that has not been included in the information set. Strong form efficient must fulfil four criteria, Barnes (2009):

- No transaction costs,
- No cost of information,
- All information is public, and
- All investors are rational investors.

In a real world, it is almost impossible to satisfy all these four conditions especially the condition regarding the rationality of investors, because it ignores the personal circumstances and personal behaviour of individuals and treat all investors same in terms of psychology and behaviour.

In chapter 6 of this thesis we discuss further the links among market efficiency, informational efficiency, random walk and other models of asset prices.

3.3 Efficiency in emerging markets

Few studies have been done concerning stock market efficiency in emerging markets, most of the studies were implemented to scrutinise the random walk behaviour and hence examine the weak-form of EMH which uses the random walk model.

It is generally thought in the stock market efficiency literature that emerging markets are more likely to be inefficient since they are classified as small-sized, thin trading and less regulated markets, see Asiri (2008), Marashdeh and Shrestha (2008), Islam and Watanapalachaikul (2005) and Mobarek et.al (2008). This perspective is supported by the empirical findings of market inefficiency in emerging markets. However, the empirical literature on African emerging markets basically has been very scanty due to the lack of data. For instance, using correlation analysis on monthly stock returns data over the period from January 1981 to December 1992, it is demonstrated that the Nigerian stock market is weak-form efficient, Olowe (1999). This fact is therefore important for understanding the dynamics of the NSM beyond the period for example, whether the NSM remains weak-form efficient in the 2000-2010 period as is explored in Chapter 6 of this thesis.

Mecagni and Sourial (1999) used Generalized Autoregressive Conditional Heteroskedasticity (GARCH) estimating methods to illustrate that the four best recognised daily indices on the Egyptian stock market specified significant departures from efficient market hypothesis.

Osei (2002) investigated the characteristics of asset pricing and its reaction to Ghana's Stock Market (GSM) annual earnings announcements. By estimating the irregular and cumulative abnormal returns of selected securities on the GSM, he found that the GSM is inefficient with regard to annual earnings information discharges to the Ghanaian market.

Simons and Laryea (2006) investigated selected African stock markets efficiency (Ghana, Mauritius, Egypt and South Africa) using data series from 1990 to 2003 in weekly and monthly terms. They employed both parametric and non-parametric tests to determine weak-form efficiency of these markets. Their findings show that with the exemption of South Africa, all African stock markets in the sample are weak-form inefficient.

Most of the financial market related research has been conducted in the developed nations probably because of the ease of availability of reliable data. However, with the rise of developing nations, researchers are expressing great interest in researching emerging markets. In the field of EMH, researchers have investigated the existence of informational efficiency of these emerging markets. The table below summarises the findings of some of these researches:

Table 3-1 : shows markets studied by various researchers in different countries

Researcher	Market studied	Outcome
Barnes (1986)	Malaysia	Inefficient
Panas (1990)	Greece	Efficient
Antoniou, Ergul, and Holmes (1997)	Turkey	Improving efficiency with time.
Dickinson and Muragu (1994)	Kenya	Efficient
Urrutia (1995)	Latin American markets	Inefficient with Random Walk model and weak form efficient with runs test.
Ojah and Kermera (1999)	Latin American markets	Efficient with Random Walk model and weak form efficient.
Grieb and Reyes (1999)	Brazil	Random walk.
Harvey (1995) and Claessens et al. (1995)	Emerging markets	Inefficient.
Bailey et al. (1990)	Emerging Asian markets	Inefficient.
Bessembinder and Chan (1995)	Emerging markets	Technical signals may have some predictive power.
Haque et al. (2001)	Seven Latin American emerging markets	Latin American markets have shown remarkable performance using return to risk measures; predictability seems mixed and has volatility clustering with shocks that decay with time.
Haque et al. (2004a)	10 Asian stock markets	Inefficient

As the findings of the researchers indicate, researchers have reported mixed findings regarding efficiency of emerging markets. Some researchers have reported different findings for different time periods or for different methodologies which indicates that:

- Emerging markets although not as efficient as developed markets have been improving over the years. This improvement can be attributed to better information systems, experienced investors, better regulatory infrastructure and improved liquidity.
- The efficiency of emerging markets as measured by researchers depends upon the methodology adopted as different methods may yield different results.

3.4 Literature on Market Anomalies

Anomalies refer to regularities that appear in the trading of stocks. Schwert (2003) expresses that Anomalies are empirical results that tend to be incoherent with the theories of asset-pricing behaviour. They refer to either market inefficiency or inconsistency of the underlying asset-pricing model.

As Islam and Watanapalachaikul (2005) explain, anomalies indicate regularities that emerge in the stocks trading. Many researchers have come across certain empirical regularities associated with stock returns, which are not predicted by any of the traditional asset pricing models. Two of the most important features of regularities are the day of the week effect and the January effect.

Calendar effects are stock market anomalies which are related to the calendar, such as the Monday or day-of-the-week effect, the January effect or monthly effect, the preholiday effect and the intra-month effect.

Cuthbertson and Nitzsche (2005) explain that the day of the week effect indicates the fact that its appearance seems to be a systematic decline in stock prices between the Friday closing and Monday opening[11]. That is also the case in the January effect. The daily rate of return on stocks tends to be high during the first week in January[12].

[11] According to Cuthbertson and Nitzsche (2005, p433-434) one explanation of the weekend effect is that firms and governments release 'good news' between Monday and Friday but wait until the weekend to release bad news. The bad news is then reflected in low stock prices on Monday. However, in an efficient market, some agents should recognise this and should (short) sell on Friday (price is high) and buy on Monday (price is low), assuming that the expected profit more than covers transactions cost and payment for risk. This action should lead to a removal of the anomaly.

[12] For more literature see also Avramov and Chordia (2006), Lewellen and Nagel (2006).

In modern day research in market efficiency, studying anomalies is essential. The term stock market anomaly is given to any characterization of stock market behaviour of security prices and/or returns which seemingly contradicts the efficient market hypothesis. Fama and French (1996) define anomalies as patterns in stock price movement which cannot be explained by Capital Asset Pricing Model. However, Damodaran (2002) warns that anomalies should be considered in context of any tests because the tests themselves could have some problems leading to false outcomes of market anomaly.

In chapter 8 of the thesis, we discuss more technical perspectives on anomalies. These perspectives relate to the models typically used in analysing market data for evidence of anomalies. Table 3.2 below summarises different kinds of anomalies investigated by researchers between 1980 and 2005 and their findings.

Table 3-2 : shows anomalies by various researchers and findings

Anomaly	Researcher(s)	Finding(s)
Month-of-the-year/ January effect	Haugen and Jorion (1996)	The stock prices in the first half of January are generally higher than that in December previous year.
Turn-of-the-year effect	Givoly and Ovadia (1983)	Trading volume of poorly performing stocks is higher in December.
	Guin (2005)	For taxation purposes there is higher volume of selling in December and higher rate of buying in January.
Month of the quarter effect	Penman (1987)	Stocks usually provide higher returns in the first month of the quarter.
Week-of-the-month effect	Hensel and Ziemba (1996)	Stocks usually provide higher returns during the first week of the month compared to the rest of the month.
Day-of-the-week/ weekend effect	French (1980)	On average closing prices on Monday are lower than closing prices on Friday.
	Guin (2005)	Weekend effect can be attributed to the fact that firms/governments tend to release bad news over the weekend in order to prevent a run.
	Foster and Vishawanathan (1990)	Information asymmetry leads to rising trading volumes on Fridays and decreasing trading volumes on Monday.
Monday effect	Barone (1990)	Average returns on Monday are lower than any other day of the week. Monday and Tuesday witness the largest decline in stock prices.
Hour-of-the-day/end-of-the-day effect	Guin (2005)	The trading volumes tend to rise during the final quarter hour of trading time.
	Harvey and Huang (1991)	There is higher interest rate volatility during the first trading hour of the last two days of the week.
Holiday effect	Pettengill (1989)	Stock returns tend to increase before public holidays.
Political cycle effect	Santa and Valkanov (2003)	Stock market returns are on average higher during the first and last year of presidential term.

Few studies have been done on African and Middle East Markets. Alagidede (2008b) studied month-of-the-year and pre-holiday seasonality in African stock markets, namely: Egypt, Kenya, Morocco, Nigeria, South Africa, Tunisia and Zimbabwe. He studied the two most popular calendar effects, the month-of-the-year and the pre-holiday effects and their inference for stock market efficiency. His methodologies were the traditional approach of modelling anomalies using OLS regressions as well as examining both the mean and conditional variance. His finding indicates that the month-of-the-year effect is prevalent in African stock returns. High and significant returns were found in days preceding a public holiday for South Africa.

Chukwuogor (2008) investigates the presence of day-of-the-week effect and returns volatility and analyses the annual returns of five African stock markets namely Botswana, Egypt, Ghana, Nigeria and South Africa. He used a set of parametric and nonparametric tests to test equality of mean returns and standard deviations of the returns across the-day-of-the-week. His findings disagree with the presence of the-day-of-the-week effect but indicate insignificant daily returns volatility in most of these Markets.

Bley and Saad (2010) analyzed daily market index and company level stock return data across the Gulf Cooperation Council (GCC) region in search of calendar effects well documented in many international stock markets. The presence of day-of-the-week anomalies suggests the existence of a global phenomenon.

3.5 Further notes on Stock Market Volatility

Many definitions have been given to the term of volatility in financial market. By searching in Google a large number of definition such as: Volatility is the variation of the price of a security from day to day or even month to month or year to year. A common way to calculate it is to take the standard deviation of the last 20 days. The daily calculation value is the one used often in the options markets. Volatility is the rate at which the price of a security moves up and down and it is found by calculating the annualized standard deviation of daily change in price. If the movements of stock prices go up and down rapidly over short periods of time, it has high volatility. If the prices almost do not change, the volatility is low.

In other words, it refers to the amount of uncertainty. Higher volatility means that the value of the security may be distributed over a greater range of values, which means the price of the security can change dramatically over a short period of time in either direction. Where lower volatility means the value of security cannot fluctuate dramatically, but changes in value steadily over a period of time.

Volatility modelling plays a very important role in financial and econometric researches as volatility is a primary factor for risk management. Stochastic volatility models are used in the field of quantitative finance to evaluate derivative securities, such as options. The name derives from the models' treatment of the underlying security's volatility as a random process, governed by state variables such as the price level of the underlying, the tendency of volatility to revert to some long-run mean value, and the variance of the volatility process itself, among others.

Volatility is a strong influence of fluctuations in the price of the shares, bonds or other financial instrument, usually associated with the high trading volume. Volatility is sometimes caused by weak earnings forecasts from some unexpected bad news for companies in an industry, or external events such as expectations of war or political unrest. Moreover, in developing markets such as the NSM high volatility is often associated with thin trading except where there is significant information flow in the market which is not evident in the NSM. Other market imperfections discussed in Chapter 2 of the thesis contribute to volatility in emerging markets for example lack of transparency in the market whereby investors' reactions to market news may be distorted by misinformation and unbalanced effects of changes in oil prices in Nigeria, for instance. These ideas are further discussed in chapters 7-9 of the thesis.

Stock market volatility modelling and forecasting have been the core of enormous theoretical and empirical investigation over the recent years by researchers alike. There are numerous incentives behind this fact. Debatably, volatility is considered one of the most essential concepts in finance world. Volatility, whether computed by standard deviation or variance of returns, is more frequently used as a rudimentary evaluation of the overall risk of financial assets. Many value-at-risk models for assessing market hazard need the evaluation or forecast of a volatility parameter. The stock market volatility prices also come directly into the Black-Scholes formula for deriving the traded options prices.

3.5.1 Emerging Stock Markets Volatility

As known from the literature that emerging stock markets are characterized by high volatility. On the one hand, markets may become informative and more efficient leading to higher volatility as prices quickly react to relevant information or speculative capital may induce excess volatility.

Aggarwal et al. (1999), notes that the high volatility of emerging markets is marked by frequent sudden changes in variance. The periods with high volatility are found to be associated with important events in each country rather than global event. Before the 2007-2008 global financial crises, the crash that happened in October 1987 in United State is the only global event in the last decade that significantly increased volatility in several markets.

De Santis and Imrohoroglu (1997) focused their attention on the following questions. First, does stock return volatility change over time? If so, are volatility changes predictable? Second, how frequent are large price changes in emerging stock markets? Third, what is the relation between market risk and expected returns? Fourth, has the liberalization of emerging financial markets affected return volatility? Their results come with strong evidence of time-varying volatility. From a qualitative point of view their results resemble those of many studies on developed markets: periods of high/low volatility tend to cluster, volatility shows high persistence and is predictable. They find that volatility is considerably higher in emerging markets, both at the conditional and unconditional level. However, they do not find any relation between expected returns and country-specific risk. Finally, the prediction that liberalization would increase market volatility is not supported by the data in their sample.

Shin (2005) used both the parametric and flexible semi-parametric GARCH in mean model to examine the relationship between expected stock returns and volatility in emerging stock markets, and found that a positive relationship prevails for the majority of the emerging markets[13], while such a relationship is insignificant in most cases.

The basic finding of this study is largely consistent with the literature using a parametric GARCH-M model, where the existence of a weak relationship between risk and return is documented. The findings of this study also suggested fundamental differenc es between emerging markets and developed markets.

The nature of volatility within and across African stock markets has also been empirically examined. For instance, using a time -varying asymmetric moving average threshold GARCH (asymmetric-MA-TGARCH) model and daily stock indices for SA, Nigeria and Kenya for the period 1985 -1998, Ogum (2002) found evidence that both conditional mean and conditional variance respond asymmetrically to past innovations.

[13] These emerging markets are 6 Latin American emerging markets (Argentina, Brazil, Chile, Colombia, Mexico, and Venezuela), 6 Asian emerging markets (India, Korea, Malaysia, Philippines, Taiwan, and Thailand), and two European emerging markets (Turkey and Greece). The sample period is from January 1989 to May 2003, after the 1987 international stock market crash.

However, in the case of conditional mean, the asymmetry is reversed i.e. good news has greater impact on return than bad news of the same magnitude.

Similarly, Piesse and Hearn (2002) used the exponential GARCH model of Nelson (1991) with weekly data for the period between 1997 and 2000 to establish evidence of bidirectional transmission of asymmetric volatility among some of the sub-Saharan equity markets. However, their overall finding was that due to lack of liquidity and limited domestic participation most of the sub-Saharan equity markets were not integrated.

N'dri (2007) analyzed the relationship between stock market returns and volatility in the regional stock market of the West African Economic and Monetary Union called the Bourse Régionale des Valeurs Mobilières (hereafeter BRVM). Using weekly data on stock prices over the period from 4 January 1999 to 29 July 2005, the study tests the risk-returns trade off within an EGARCH-in-Mean framework. The study revealed that coefficients linking conditional market returns to conditional volatility are positive but statistically insignificant.

3.6 Literature on Stock Market Bubbles

Another event occurring on the stock markets called speculative bubble and before proceeding to explain the possible causes that can lead to this event and how we can measure it, the definition of this phenomenon will be given as well as a brief historical overview. Many of the studies conducted to understand what the nature of speculative Bubble is.

3.6.1 Perspectives on speculative bubbles

In many financial markets we observe periods of price behaviour referred to as speculative bubbles. A speculative bubble can be defined as the difference between market prices and the fundamental value of the assets. A speculative bubble is associated with the periods when stock prices rise to unsustainable levels, the main motivation behind this is the optimism of investors. Thus, identification of a speculative bubble is not very easy to do, because to accept or reject the existence of a bubble is linked to the basic model used in comparing observed asset values to their fundamental values.

The bibliography on definition of bubbles is too voluminous to be included here; some of these definitions include Slawski (2008, p2): "A bubble is defined as that portion of the equilibrium price over and above the market fundamental. The market fundamental is the maximum buy-and-hold-forever valuation of the asset". He added "This term usually means that the price of an asset is significantly different from what is believed to be the asset's fundamental value. Furthermore, these events are often not isolated incidents involving a single asset, but rather entire regions or sectors of the economy".
Mokhtar et al (2006, p102) state: "*A price bubble is defined as the asset price movement that is unexplainable by the fundamentals. A bubble can also be identified as a sharp rise in the price of an asset in a continuous process. Meanwhile, rational speculative bubbles can be defined as an attempt to identify the behaviour of investors who act irrationally, such as when herding occurs*".

Experience from the current financial crisis (2007-2008) suggests that investors as well as policy makers did not realise the level of speculative trading in the market until the bubbles exploded. The discovery of rational speculative bubbles in stock markets has important implications for both investors and policy makers. From the point of view of investors, even though price bubbles allow them to earn abnormal profits, the existence of price bubble itself implies the possibility of stock price crash.

This information forces the investors to act rationally by selling the assets and adjusting the share prices toward their fair value, thus making the market to be efficient. Moreover, inferring the existence and size of price bubbles provides several implications to policy makers on how to protect the market. The protection of the market may be conducted through manipulating policies in order to minimise the price bubbles in the stock market. Furthermore, as time goes, market efficiency improves. Thus, by recognizing the level of speculative trading and the size of price bubbles, specific actions can be imposed to stabilise the stock market.

Furthermore, determining the level of speculative bubbles in emerging markets is very important for the policy makers and international investors in these markets. Hassan and Yu (2006) state: for the rapidly growing frontier emerging stock markets the correct detection of rational speculative bubbles can be very important in policy-making decisions and international portfolio diversification. For example, Chan et al. (2003) explain that if rational bubbles are not present, that it is only necessary to take control of the market fundamentals. If, however, inflation is being driven by a bubble phenomenon, then positive action is needed to shock expectations from the bubble path.

Speculative bubbles are not something new in the stock market. The first famous bubbles in the history mentioned by many researchers[14] occurred in Holland. The bubble called "tulip bubble " and it happened early in the 17th century. The bubble was followed by the collapse of its share and its issuing company. Other bubbles such as the South Sea and Mississippi bubbles that occurred in 1717 -20 which was defined as the first international crisis and the great stock exchange bubble in the USA in 1929.

Studying whether there are speculative bubbles in stock market has become in attractive issue for investors, academic researchers and policymakers in financial market since the existence of bubbles contribute to market inefficiency. Therefore, a number of empirical studies have been detected in recent years to identify rational speculative bubbles in stock market. The majority of those studies examining the existence of speculative bubbles are focussed on the techniques used to detect rational speculative bubbles in the stock market.

Different kinds of bubbles occur in financial markets influenced by different factors. These are: rational bubbles, near rational bubbles, intrinsic bubbles, dot com bubble, fads and informational bubbles. We note that bubbles can in this respect arise in different ways and for particular sectors of an economy; for example the dot-com bubble was specifically due to hypes in the technology industry about valuations and market potentials of new Internet technology-based companies, most of which collapsed as a result. Similarly, different financial crashes provide evidence of particular collapse of bubbles in such places as Asia (1987 crash) and sometimes for particular stocks for example the crash of Long Term Capital Management, a US investment firm, in 1998.

Attempts have been made in strategic studies of the take -up and follow-on success of failure of technology -based innovations in different industry sectors using the methodologies developed by Gartner[15], which is the world's largest technology research firm. These techniques are referred to as Gartner's hype cycles for different sectors for example technology, health, banking and investment, education, social networks, etcetera, Bresciani and Eppler (2010), Fenn et al (2009), Enescu (2010). As shown in

[14] It has been mentioned by some researcher such as: Maniatis (2009), Browning (2000), O'Hara (2008), Cuthbertson and Nitzsche (2005) and Prosperetti (2004).

[15] See: http://www.gartner.com/technology/research/methodologies/hype-cycle.jsp

Figure 3.1 adapted from Linden and Fenn (2003), a hype cycle for an industry sector such as an emerging technology has five main stages labelled as technology trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment, and plateau of productivity.

Figure 3-1: The Hype Curve

The figure shows that bubbles can be generated in sync with these stages in addition to events within the financial markets due to the upswings and downwards in the market values of the assets underpinned by the hype cycle.

Bubble is one of the key issues in stock market that has got an essential impact on the efficiency of the stock market. However, before 1980, when the EMH was being challenged, the traditional asset pricing model still did not take the bubble issue into account.

According to Brooks and Katsaris (2003, p326) "*There are several approaches to test for the presence or otherwise of speculative bubbles. These approaches can be grouped into three main categories: tests for bubble premiums, tests for excess volatility and tests for the cointegration of dividends and prices*". Among them, the Duration Dependence Test using the Log Logistic Hazard Model developed by McQueen and Thorley (1994) has been widely accepted in detecting rational speculative bubbles in stock prices. Some of these tests are used in chapter 7 to investigate the presence of bubbles in the NSM.

In the literature there is dissimilarity in the results of detecting rational speculative bubbles. Although the majority of studies do not support the existence of rational speculative bubbles in financial markets some of the studies accept the hypothesis of existence of rational speculative bubbles.

3.6.2 Studies supporting the existence of rational speculative bubbles in global and emerging markets

Parvar and Waters (2010) empirically investigated the existence of periodically collapsing bubbles in seven Middle East and North African (MENA) financial markets for the period ending in May 2009[16]. They used real monthly data for price index, market value, and dividends series from these markets. Taylor and Peel (1998) found that the hypothesis of a bubble form ation cannot be rejected for all seven markets investigated.

Mokhtar et al. (2006) reported the existence of rational speculative bubb les in Malaysian stock market before (1994-1996) and after (1999-2003) the Asian Financial Crisis 1997.

Evidence for the existence of speculative bubbles over the 1980s and 1990s was found by Binswanger (2004) using the aggregate stock price indices, industrial production indices (seasonally adjusted) and consumer price indices for Japan, the US and the four major European economies from 1960 till 1999.

A study conducted by Bohl (2003) indicates presence of rational speculative bubbles in the US stock market. He used the Enders –Siklos momentum threshold autoregressive (MTAR) model on stock prices and dividends for time period 1871–2001.

3.6.3 Studies rejecting the existence of rational speculative bubbles

Yu and Hassan (2009) employed fractional integration techniques and duration dependence tests based on the ARFIMA models and nonparametric Nelson-Aalen smoothed hazard functions in OIC[17] stock markets. In this study [18], their outcome

16 The Seven Middle East and North African countries involved in the study are, Egypt (02/25/97 to 11/25/2008), Israel (2/25/1997 to 11/25/2008), Morocco (2/25/1997 to 10/25/2008), Oman (1/25/2000 to 5/25/2009), Tunisia (1/25/1997 to 5/25/2009), Turkey(12/25/1987 to 10/25/2008) and Lebanon (2/25/2000 to 5/25/2009).

17 The OIC (Organisation of the Islamic Conference) is an intergovernmental organization grouping of 57 mostly Islamic nations in the Middle East, North and West Africa, Central Asia, Southeast Asia, the

support rejection of rational speculative bubbles in OIC stock markets. They found also that fractional integration tests do not support the possibility of rational speculative bubbles, evidenced by fractionally integrated parameter values of log dividend yields. Equally, duration dependence tests strongly reject the existence of bubbles as well, supported by non-decreasing nonparametric Nelson-Aalen smoothed hazard functions.

Jirasakuldech et al. (2006) analyze REIT prices using monthly price index by applying a vector of macroeconomic fundamentals. Using the unit root test and cointegration procedures, they find no evidence of rational bubbles in the REIT market. Tests for duration dependence in the returns series show no evidence of negative duration dependence, suggesting that REIT markets are not affected by rational bubbles.

Koustas and Serletis (2005) conduct tests for fractional integration in the S&P 500 log dividend yield; their findings, based on tests for fractional integration, yield robust rejections of the null hypothesis of rational bubbles. Their results strongly suggest that the log dividend yield is mean reverting.

3.7 Summary

The above literature review explored key issues which characterise the behaviour of stock markets. The issues are: market efficiency, bubbles, anomalies and volatility. It is noted that many of these issues are linked to market efficiency.

The main focus of the chapter is on different meanings and approaches used in studying these issues. The evidence for the existence of the issues in emerging markets are examined, particularly in African stock markets. The implications of the issues for stock market performance are discussed in the chapter, hence their importance in this research.

Indian subcontinent and South America. These OIC member countries decided to promote Islamic solidarity by coordinating social, economic, scientific, and cultural activities.

[18] They used price indexes of 14 OIC stock markets of Indonesia (1990:01–2003:03), Malaysia (1985:01–2003:03), Turkey (1987:01– 2003:03), Bahrain (1999:01–2003:03), Egypt (1996:01–2003:03), Jordan (1979:01–2003:03), Morocco (1996:01–2003:03), Oman (1999:01– 2003:03), Saudi Arabia (1998:01–2003:03), Tunisia (1996:01–2003:03), Bangladesh (1996:01–2003:03), Pakistan (1985:01–2003:03), Nigeria (1985:01–2003:03), and Côte d'Ivoire (1996:01–2003:03).

CHAPTER 4: DATA AND METHODOLOGY

4.1 Introduction

This chapter sets out the research methodology and nature of data used to investigate the research objectives and questions which are outlined in Chapter 1. For this purpose, after a brief description of the data and selected data analysis software below, we recall the research objectives and questions for easy follow-through of the methodology.

4.2 Data and Computer Programs

4.2.1 Data

The stock data is obtained from Global Financial Data (GFD), which is a company registered in the USA and specialises in providing financial statistical database. This research will test stock returns of the NSM during the period January 2000 to December 2010. Besides the full sample period, another two sub-periods are also included in the study namely pre-reforms period (2000-2004) and post-reforms period (2005-2010). Further, based on global financial crises which took place in the middle of 2007, the post-reforms period also divided into two other period including pre-crisis period (2005-July 2007) and post-crisis period (August 2007-2010). We hypothesize that the general statistical characteristics are different between the three periods, because of the reforms and the global financial crises.

Most of the existing studies in the literature have used daily, weekly and monthly indexes and returns to examine the general characteristics of a stock market.

In this research the data was collected through the internet by buying an access to GFD. Access to this kind of secondary data is increasingly becoming available in electronic form. Sometimes it may be useful in its original form or we may have to change its format to fit our needs. In this case most of the data was available in electronic form, ready to be downloaded and easy to fit any statistical software.

As noted in Chapter 1, this research investigates different stock market issues and each issue has its own methods and models and may require different configurations of the data for example daily, weekly, monthly or yearly data. For example, to study the movement of the overall NSM index, *monthly* data were used and for descriptive statistics methods and models *monthly, weekly, yearly and daily* returns data of the

NSM are used. Similarly for testing NSM efficiency *daily and monthly* returns were used, and so on. The appropriate data configurations for the different issues are summarised in a general framework for the methodology presented in Figure 4.1.

4.2.2 Selection of Eviews Software Program

A large number of statistical programs are available for analysing the NSM data including EVIEWS, MATLAB, STATA, SAS, SPSS, R, EXCEL, etc. The main computer package used in this research is EViews supported by EXCEL spreadsheet analysis.

The justification for selection of EViews (Econometric Views) is that it is a statistical package for windows, used mainly for time-series oriented econometric analyses. It is developed by Quantitative Micro Software (QMS). It can be used for general statistical analysis and econometric analyses such as cross-section and panel data analysis and time series estimation and forecasting.

Additional software used in the study includes SPSS (PASW) and Stata.

4.3 Overview of the Research Methodology by Objectives and Research Questions (RQs)

4.3.1 Linking the Research Objectives and Questions

The overall methodology for the research discussed in this chapter is visualised in Figure 4.1 below and shows the links among the research strategy, objectives, questions, key stock market issues and thesis chapters.

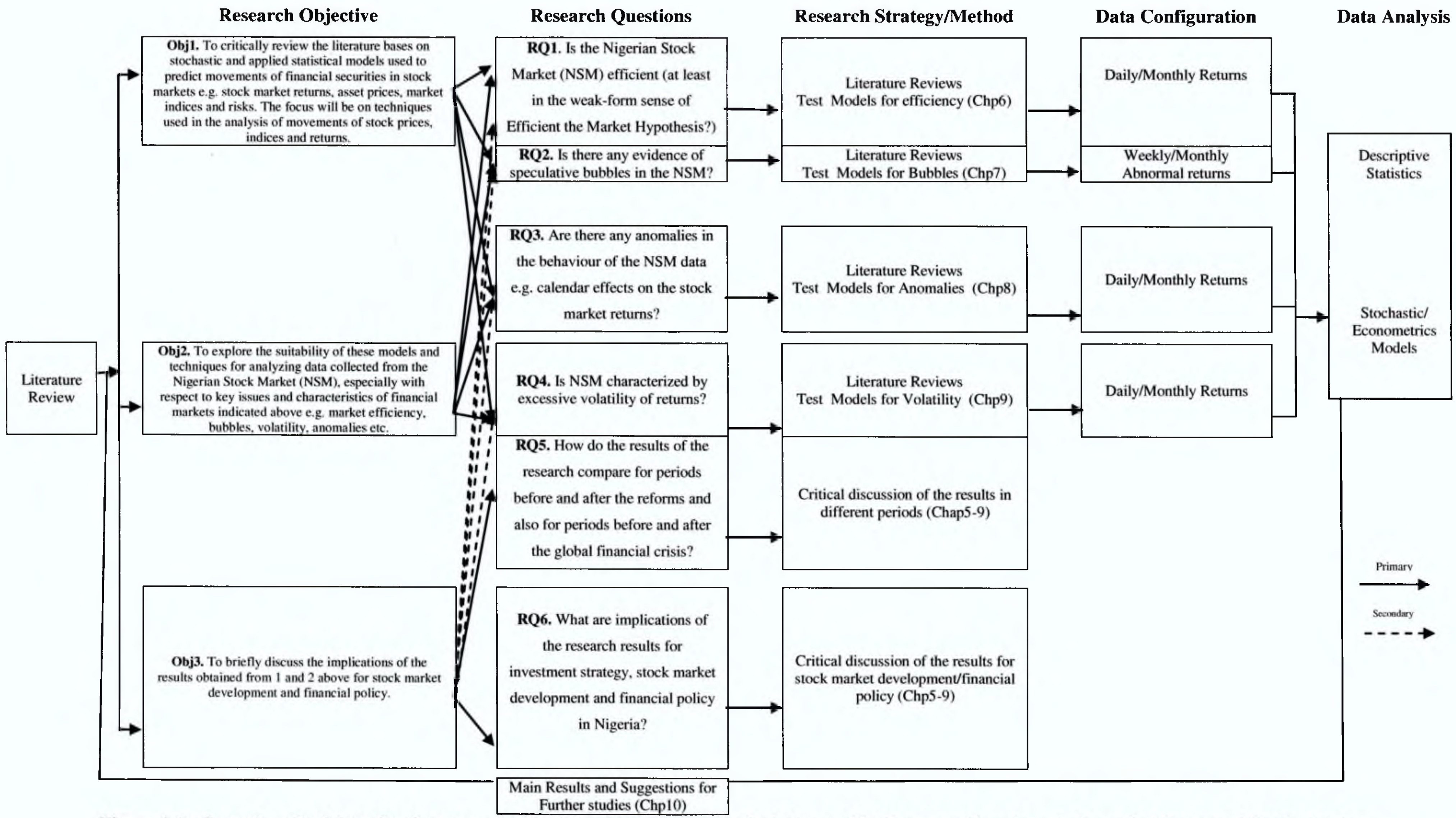

Figure 4-1: Overall methodology for the research with links among the research strategy, objectives, questions, key stock market issues and thesis chapters

It should be noted that the data available for some of the above periods may not be adequate to support the analysis of some of the issues. For instance, the data on bubbles is only adequate for investigating the presence of bubbles for the whole period as well as pre- and post-reforms, not pre- and post-crisis.

4.3.2 Summary of the Research Methodology by Objectives and Questions

Objectives 1 and 2 (RQs 1-4)

To investigate Objective 1 we use insights from the general literature on the various models and techniques to analyse the key characteristics discussed in the general literature review in Chapter 3. This insight is combined with technical review of the models and techniques in specific chapters on the key issues (Chapters 6-9 for market efficiency, bubbles, anomalies and volatility, respectively).

Objective 3 (RQs 5 and 6)

To investigate this objective we discuss the implications of the descriptive statistics and general characteristics of NSM data obtained in Chapter 5 for stock market development and financial policy.

By comparing the behaviour of the stock market before and after financial reforms and crisis (as stated in RQ 5), the discussion examines the impact of the reforms and crisis on stock market development and financial policy. Hence, it suggests the nature of reforms and financial policies that will improve the development of the NSM. These discussions of results are based on the background information on the NSM and Nigerian financial system presented in Chapter 2.

Also, for this objective, we discuss the implications of the results on the key issues obtained in each of the Chapters 6-9 for stock market development and financial policy. The discussions will reinforce the relevance of the key issues to stock market performance already mentioned in Chapters 1 and 2.

In brief, the research methodology is a mixed approach which combines insights from critical reviews of literature in Chapters 3-9, background information on the Nigerian financial system, descriptive statistics and general characteristics of the NSM index and returns, and stochastic modelling of four key issues in stock market analysis.

The following notes summarise the statistical models used in the data analysis and modelling chapters (5-9).

4.3.3 Summary of Methods in Key Chapters

Descriptive statistics and general characteristics of NSM data (Chapter 5)

In this chapter we obtain the statistical characteristics of the NSM data (All Share Index and Returns) using relevant summary statistics namely mean, median, standard deviations, skewness and kurtosis. We interpret what these characteristics mean in financial statistics and particularly stock market behaviour.

We also analyse the behaviour of the data using some univariate time series models namely moving average models for example single and triple moving averages, and single, double and Holt Winters exponential smoothing models. The rationales for these models are explained in the chapter.

RQ1- Is the NSM efficient? (Chapter 6: Efficiency Models and Tests)

This chapter reviews the concepts and importance of market efficiency to stock market performance. There is also a more technical review of statistical models and tests used in investigating market efficiency. These tests include Dickey-Fuller tests and Phillips-Perron tests for stationarity of time series data, the Jarque-Bera and related tests for normality, and linear/non-linear tests of market efficiency such as autocorrelation and Q-statistics, run tests, and Brock-Dechert-Scheinkman (BDS) tests. The chapter applies some of these tests to the NSM data across different periods.

RQ2 - Is there evidence of bubbles in the NSM? (Chapter 7: Rationale Speculative Bubbles)

In this chapter there is a review of the concepts and importance of bubbles to stock market performance. There is also a more technical review of statistical models and tests used in investigating bubbles. These tests include duration dependent tests for example Discrete Log Logistic and Weibull Hazard Model tests as well as use of higher order moments (skewness and kurtosis). The chapter applies some of these tests to the NSM data for the overall and pre- and post-reform periods.

RQ3 - Are there any anomalies in the behaviour of the NSM data? (Chapter 8: Anomalies Studies)

This chapter discusses the concepts and importance of anomalies to stock market performance, including a more technical review of statistical models and tests used in investigating anomalies. These tests include use of summary statistics to determine existence of Monday and January effects, parametric tests of anomalies (for example, ANOVA) and nonparametric tests (Kruskal-Wallis test). The chapter applies some of these tests to the NSM data across different periods.

RQ4- Is the NSM characterised by excessive volatility? (Chapter 9: Volatility Studies)

In this chapter there is a review of the concepts and importance of volatility to stock market performance. There is also a more technical review of statistical models and tests used in investigating volatility. These tests include Exponentially Weighted Moving Average (EWMA) models, Stochastic Volatility (SV) models, Autoregressive Conditional Heteroscedasticity (ARCH) models, and Generalised ARCH (GARCH) models. The chapter applies some of these tests to the NSM data across different periods.

4.4 Summary

The chapter describes the overall methodology underlying this study linked to the research objectives and questions. It summarises the nature of data and explains that some of the key issues investigated require different configurations of data in their analyses for example daily, weekly, monthly and yearly data, depending on the models used. The chapter also summarises the types of statistical models used in the descriptive analysis of NSM data as well as technical modelling of the key issues.

CHAPTER 5: DESCRIPTIVE STATISTICS AND GENERAL CHARACTERISTICS OF THE NSM

5.1 Introduction

This chapter describes the behaviour of the NSM data using the All Share Index (stock index) for the entire market and corresponding values of market returns from period to period derived from the index. A stock market index measures the performance of the entire stock market if is obtained for the whole market or groups of related stocks if it is obtained for selected stocks in specific sectors of the market. For example, apart from the All Shares Index, an index can be calculated for stocks in financial services (banks, insurance companies, etc) or manufacturing sectors of a market.

As shown in equation 5.1 below, a stock index can be computed by comparing the current total market value of the issued shares of the constituent stocks in a particular day *t* with the corresponding value on the previous day *t*-1 as follows:

$$\mathrm{I_t} = \frac{\sum \mathrm{MC_t}}{\sum \mathrm{MC_{t-1}}} \times 100 \qquad \text{Equation 5-1}$$

where MC is the market capitalization of constituent stocks on different dates with base date $t - 1$. Hence, the stock index measures the rates at which the market changes in value from day to day.

The weekly, monthly or stock market indexes are obtained from the daily index by selecting each particular day (for example, Monday or Wednesday of every week, particular days in the middle of the month or last day of each month which are not weekend days (for example, 14^{th}, 15^{th} or 16^{th} of the month). For the yearly index the last working day in the year is typically chosen.

A stock market return measures the relative change in stock market index from period to period and is given by:

$$R_t = ln\,(\frac{I_t}{I_{t-1}}) \times 100 \qquad \text{Equation 5-2}$$

where *ln* is the natural logarithm of the ratio of indexes.

In this chapter two different techniques will be used to investigate the empirical characteristics of the NSM. Firstly, in order to describe the central tendency, dispersion and shapes of frequency distributions of NSM data, descriptive statistics of the NSM returns are obtained such as the mean, median, skewness and kurtosis. The NSM returns data are also tested for normality using the Jarque-Bera test; it is widely used for testing normality of data because it incorporates both skew and kurtosis. It can be represented as:

$$\mathrm{JB} = \frac{n}{6}\left[S^2 + \frac{(k-3)^2}{4}\right] \sim \chi_2^2 \qquad \text{Equation 5-3}$$

where n = sample size; S = skewness and k = kurtosis. Under a null hypothesis of normality of returns, the statistic follows a chi-square distribution. So we reject normality of returns at 5% level of significance if the p-value of the observed value of JB is less than 0.05 and accept otherwise.

Secondly, univariate time series econometric models such as the moving average, exponential smoothing and Holt Winters models are used to investigate the empirical characteristics of the NSM.

Understanding how the distributions of stock index and returns vary across different periods enables us to describe the impacts of financial reforms or the global financial crisis on the NSM. For example, different values of the standard deviation for different periods indicate the relative volatilities of the data for the periods. Some stochastic models of financial market data assume normality, so the tests of normality obtained in the chapter helps in determining the validity of some tests to be used in modelling the NSM data in subsequent chapters.

5.2 Data

In financial research, stock market data is mostly categorised as daily, weekly, monthly, quarterly and yearly. Stock market index for any of these periods is computed using different formulae. In this research the daily, weekly and monthly indexes of the NSM were observed from January 2000 to December 2010 and used to calculate the daily, weekly, monthly and yearly stock returns as stated in Equation 5.2 above.

The data analysis is then conducted by segmenting the data in three periods. The first is overall period which covers data from January 2000 to December 2010. The second period is January 2000 to December 2004 which is regarded as pre-reforms period[19]. The third period is January 2005 to December 2010 which represents the post -reforms period. Hence, it is *hypothesized that the general statistical characteristics of the NSM are different among the three periods, because of the 2004 reforms and the 2007 global financial crisis.*

However, to determine the effect of the global financial crises the third period is divided in two periods, the first period from January 2005 to end of July 2007 is referred to as pre-crisis period, and the second period from 1 August 2007 to end of December 2010 represents the post-crisis period. In this research we consider the end of July 2007 as the start of the global financial crises, following the date pointed out by some researchers in the field. According to Martin and Milas (2009, p. 1) "*The global financial crisis that began in July 2007 looks set to run for some time and to have profound effects on the global economy. The magnitude of the event and the scale of the disruption have led to much speculation as to the deeper causes of the crisis*".

This start date of the crisis is also supported by several researchers including Coudert et al (2010), Seth (2009) and Brunnermeier (2009)[20]. Moreover, it is known that the crisis was built up from years 2005-2006 but culminated in the year 2007 when the American mortgage market and underpinning market securitization forced potential and actual collapses on the part of some financial firms in the US (for example, AIG, Bear Stearns and Lehman Brothers), Ezepue and Solarin (2008) and chapter 9 of this thesis as revealed by ARCH/GARCH volatility modelling in NSM returns.

A sample of the daily index and returns data for year 2001 is shown below based on the first five results.

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[19]In July 2004, the former Governor of the Central Bank of Nigeria (CBN), Professor Charles C. Soludo lunched the biggest reforms on Nigerian Banking sector (for more details refer to chapter two).
[20] For more support see the following links:
http://www.voxeu.org/reports/subprime/report.pdf
http://www.sesric.org/files/article/400.pdf

Table5-1 Sample daily index and returns data for 2000 (first 5 results)

Date	Index (I)	Return (R)
01/04/2001	8229	1.4443
01/05/2001	8285.4004	0.6830
01/08/2001	8315	0.3566
01/09/2001	8377.2002	0.7453
01/10/2001	8573.7998	2.3197

We illustrate the returns calculations as follows. For t = 05 January 2001 (01/05/2001) and $t\text{-}1$ = 04 January 2001 (01/04/2000),

$$R_t = \ln\left(\frac{I_t}{I_{t-1}}\right)\times 100 = \ln\left(\frac{8285.4004}{8229}\right)\times 100 = 1.4443$$

The weekly index and returns are chosen as the Wednesday results for each week. The monthly index and returns are chosen as the results for the last working day in the month. Similarly, the yearly data are taken as the results for the last working day in December of each year.

Figure 5.1 and Figure 5.2 below display the daily and monthly returns graphically.

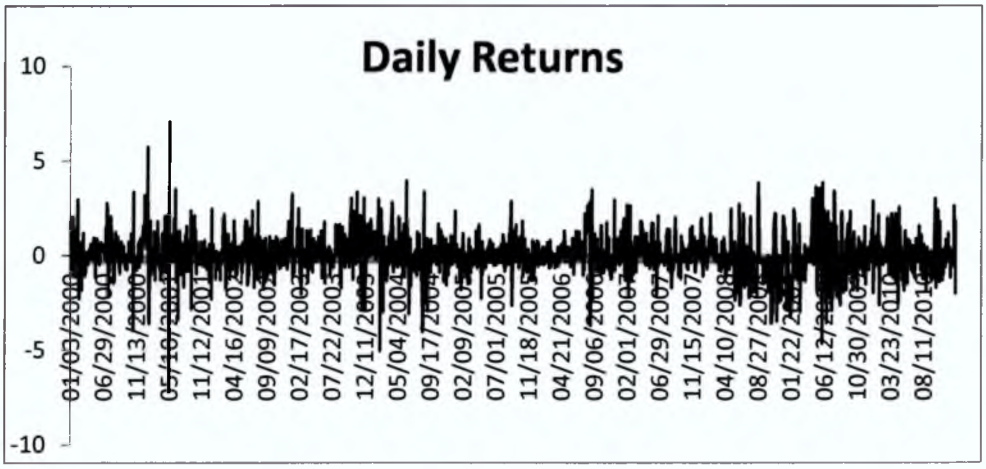


Figure 5-1 : Daily returns, 2000-2010

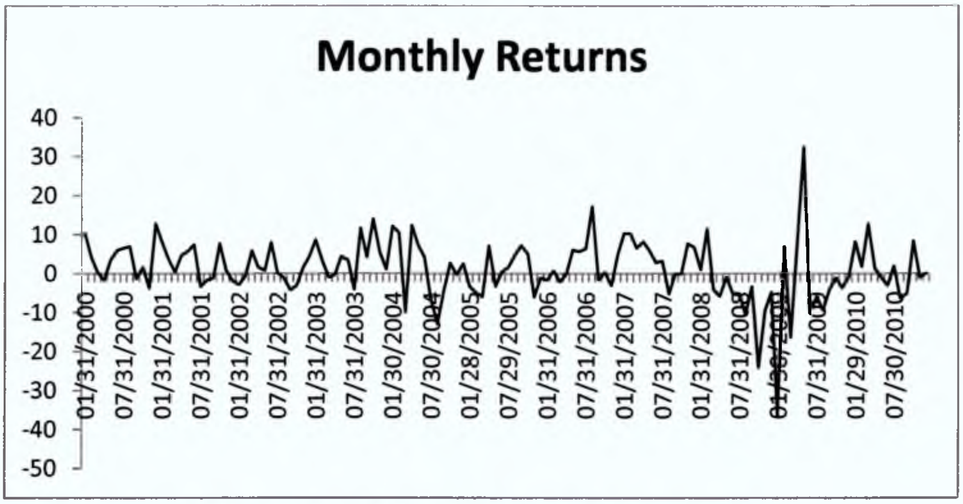


Figure 5-2 : Monthly returns, 2000-2010

As can be seen from the figures above, NSM returns such that the period from 2000 to 2003 shows low density in term of market activity compared with the period 2004 to 2010, which indicates a higher density. Low trading activity has been mentioned in Chapter 2 as a characteristic of undeveloped markets; generally in developed markets such as US and UK financial traders are very active and their activity results in high trading density.

In addition, Figure 5.5 on volatility of monthly returns shows that stock returns highly fluctuated between May 2003 to October 2010, which are years of high volatility in the market.

5.3 Descriptive Statistics for the Returns

In this section we obtain the summary statistics of the returns data based on the following measures of average, dispersion, skewness and kurtosis. The mean (μ) is the simple average of returns given by

$$\mu = \frac{\sum R}{n} \qquad \text{Equation 5-4}$$

where R the observation returns (stock market returns) n the number of observations.

The median is the middlemost return in a range of returns being summarised another measure of central tendency. Comparing the median with the mean gives one a first idea of the shape of the distribution. For instance, if the distribution is approximately normal or symmetrical, the mean and median will be nearly equal in value. The median could be calculated as:

$$Median = L + i\left(\frac{n/_{2} - F}{f}\right) \qquad \text{Equation 5-5}$$

where L the lower boundary of the median class, i is the width of the median class, F the cumulative frequency up to lower boundary of the median class, and f is the frequency in the median class.

The Standard deviation(σ) has wide applications in finance as a measure of risk and uncertainty and is used as a measure of daily and monthly stock market volatility in the NSM. Standard deviation can be computed by:

$$\sigma = \sqrt{\frac{\Sigma(R_{it}-\mu)^2}{N_t}} \qquad \text{Equation 5-6}$$

where there are N_t monthly or daily returns R_{it} in month or day t. As explained before in the chapter, the monthly data were obtained from the daily data through a systematic sampling of last trading day in the month. This procedure is common practice in the literature on financial modelling as well as the global financial data from which our data were sourced, Taylor and Tonks (1989), Nguiffo-Boyom (2008), Siliverstovs (2012). An alternative approach would be to average out the daily data to obtain the monthly data. In this case, there would be from statistical theory a symbolic connection between the monthly standard deviation and the daily standard deviation of returns (the monthly deviation will be the daily deviation divided by the square root of the contributing sample size given by the number of trading days in the month).

For skewness, we recall that in financial analysis a negative skewness means that there is a high probability of significant negative returns (that is the distribution of returns has a long tail to the left). Positive skewness means the distribution of returns has a long tail to the right so that there is a high probability of a positive return. Skewness can be defined as:

$$Skewness = \frac{\Sigma f(R-\mu)^3}{\sigma^3} \qquad \text{Equation 5-7}$$

Kurtosis measures the degree of peakedness of the distribution or the fatness of the tails of a probability distribution. High kurtosis means that a distribution is highly peaked with thicker tails than one with a lower kurtosis. Kurtosis can be computed by using the following formula:

$$Kurtosis = \frac{\mu_4}{\mu_2^2} = \frac{\sum f(R-\mu)^4}{\left[\sum f(R-\mu)^2\right]^2} \qquad \text{Equation 5-8}$$

where μ_4 is the 4^{th} central moment, μ_2 the 2^{nd} central moment. The kurtosis of a normal distribution measured from the above equation is 3 so that we can compare the calculated kurtosis with 3 to indicate to what extent the returns distributions are normally distributed.

Tables 5.2-5.6 present the above summary statistics and the Jarque-Bera test statistics with their p-values from the daily, weekly and monthly return series of the NSM, respectively, over the study period January 2000 to December 2010. Software used in this section includes EVIEWS 7 and EXCEL 2007.

Table 5-2 : Descriptive statistics for daily return on the NSM all share Index

Period	Mean	Median	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	Probability
Jan 00 - Dec 10 Overall	0.0599	0.0000	1.0713	-0.0194	6.3999	1248.559	0.0000
Jan 00 - Dec 04 (Pre- Reforms)	0.1341	0.0258	1.0573	0.1786	9.1428	1782.633	0.0000
Jan 05 - Dec 10 (Post- Reforms)	0.0026	-0.0003	1.0926	0.0240	4.5857	153.3081	0.0000
Jan 05 - July 07 (Pre- Crises)	0.1287	0.0000	0.8390	0.1424	6.1144	253.0700	0.0000
Aug 07 - Dec 10 (Post- Crises)	-0.0905	-0.0659	1.2395	0.1179	3.8381	26.5628	0.0000
2000	0.1939	0.0566	0.9020	0.0089	3.2768	166.9102	0.0000
2001	0.1633	0.0001	1.3414	0.6468	12.3309	709.9069	0.0000
2002	0.0439	0.0000	0.8202	0.4316	3.8371	13.9780	0.0009
2003	0.2155	0.1024	1.0266	0.2305	4.4325	22.0801	0.0000
2004	0.0676	0.0071	1.1523	-0.4848	5.8757	97.08699	0.0000
2005	0.0042	-0.0004	0.7254	0.2496	5.3123	56.4269	0.0000
2006	0.1325	0.0000	0.8893	-0.0579	7.7533	227.9521	0.0000
2007	0.2335	0.0279	0.8343	0.2529	3.7247	7.7785	0.0205
2008	-0.2497	-0.3543	1.2574	0.1041	3.7270	5.8382	0.0540
2009	-0.1669	-0.2937	1.5598	0.2966	3.0338	3.6341	0.1625
2010	0.0702	0.0404	0.9816	0.1427	3.5462	3.9097	0.1416

Discussions of results for daily returns

The mean daily returns during the overall period are less than those for pre-reform and post-reform/pre-crisis periods (0.06%, 0.13% and 0.13%), respectively. This shows that the NSM performed poorly as a result of the global financial crisis.

The results for individual years show the effects of reforms and crisis more clearly. The results for the two years 2006 and 2007 after the reforms but before the crisis (0.13% and 0.23%, respectively) are much higher than the first two years 2004 and 2005 of the reforms (0.07% and 0.00%, respectively). This shows that the reforms took about two years to impact the NSM positively.

The returns for two main years of the crisis 2008 and 2009 (-0.25% and -0.17%, respectively) are much lower than those for any other years. Hence, the financial reforms have positive overall effect on the NSM and global financial crisis have negative overall effect.

Similarly, as measured by the standard deviations of daily returns, the post-reform/pre-crisis period (2005-July 2007) has the lowest volatility (0.84%) for the entire study period and the post-crisis period (August 2007-2010) has the highest volatility (1.24%) for the study period. Hence, the reforms have made the stock market more stable (therefore less risky for investors) and the crisis has made the stock market more volatile and therefore more risky for investors. Again these conclusions are supported by the low standard deviations in the individual years (0.73%, 0.89% and 0.83% in years 2005-2007) and (1.26% and 1.56% in years 2008 and 2009).

The above facts are illustrated graphically in Figure 5.3 below

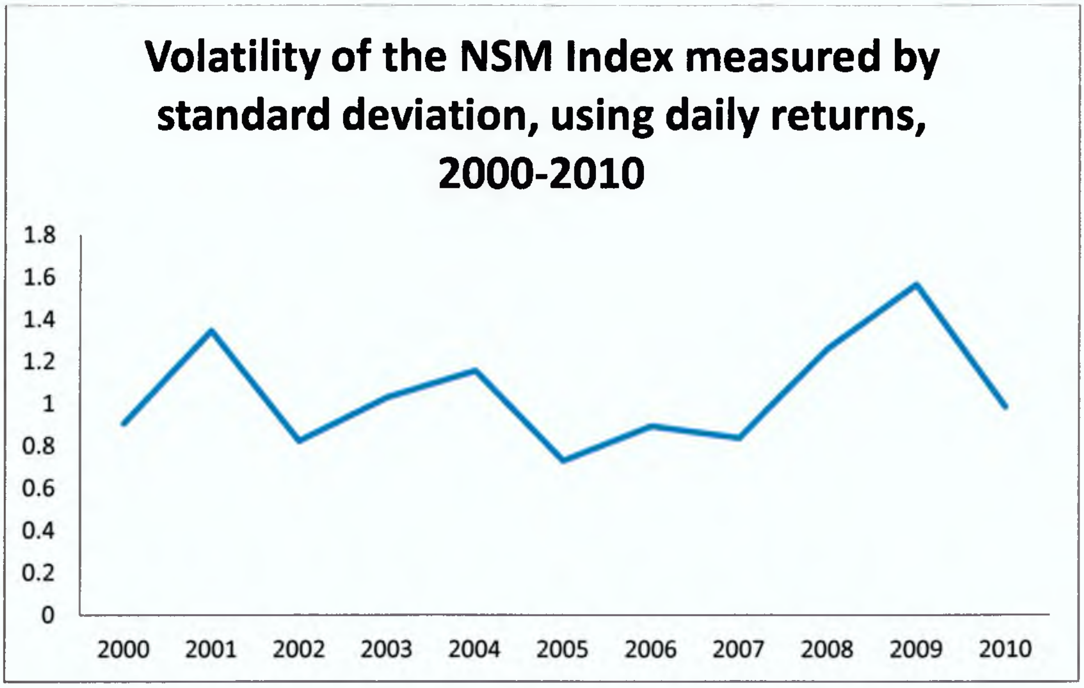


Figure 5-3 : Volatility of the NSM Index measured by standard deviation, 2000 -2010

The data results for skewness show that most of the daily returns are positively skewed. The kurtosis results show that the distributions are leptokurtic (with kurtosis values much larger than normal kurtosis 3) for all the periods and most of the years. This shows that in general daily returns in the NSM are not normally distributed. The Jarque-Bera test shows that only three years daily data are normally distributed at the 5% level of error (years 2008-2010).

Table 5-3 Descriptive statistics for weekly return on the NSM all Share Index.

Period	Mean	Median	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	Probability
Jan 00 - Dec 10 Overall	0.2720	0.3014	3.2411	-0.4581	5.6239	183.4532	0.0000
Jan 00 - Dec 04 (Pre- Reforms)	0.5788	0.4482	2.7667	-0.1986	5.6320	75.8711	0.0000
Jan 05 - Dec 10 (Post- Reforms)	0.0200	0.1392	3.5687	-0.4658	5.1621	72.2822	0.0000
Jan 05 - July 07 (Pre- Crises)	0.6030	0.4517	2.5977	-0.0597	8.9321	198.0233	0.0000
Aug 07 - Dec 10	-0.4220	-0.1359	4.1092	-0.3335	3.8667	8.8705	0.0119
2000	0.8736	0.7550	2.2559	0.3446	3.1641	1.0667	0.5866
2001	0.5700	0.1738	2.4308	1.0485	4.7162	15.6035	0.0004
2002	0.1623	-0.1394	2.2901	0.6757	3.3759	4.1809	0.1236
2003	0.9673	0.6497	2.8193	-0.2175	3.9561	2.3906	0.3026
2004	0.3086	0.4924	3.7498	-0.7363	5.3198	16.3593	0.0003
2005	0.0876	-0.1269	2.2612	0.8676	4.9863	15.3615	0.0005
2006	0.6165	0.1919	3.0769	-0.4956	10.1309	112.3030	0.0000
2007	1.0354	0.7182	2.1804	0.2046	3.0897	0.3804	0.8268
2008	-1.1836	-1.5255	4.5743	-0.1116	3.4576	0.5617	0.7551
2009	-0.7757	-0.0191	5.2858	-0.0956	2.6479	0.3479	0.8404
2010	0.3390	0.2423	2.4431	0.1635	2.3906	1.0362	0.5956

Discussions of results for weekly returns

Similarly to the finding of the mean daily return, the mean weekly returns during the overall period are less than those for pre-reform and post-reform/pre-crisis periods (0.27%, 0.58% and 0.60%), respectively. The table also shows that the NSM performed poorly during the post-reform years (with mean return 0.02%) as a result of the global financial crisis.

The results for individual years also show the effects of reforms and crisis more clearly. The results for the two years 2006 and 2007 after the reforms but before the crisis (0.62% and 1.04%, respectively) are much higher than he first two years 2004 and 2005 of the reforms (0.31% and 0.09%, respectively).

The clear impact of the global financial crises can be seen from the mean returns for the two main years of the crisis 2008 and 2009 (-1.18% and -0.78%, respectively) which are much lower than those for any other years.

As shown in the fourth column the post-reform/pre-crisis period (2005-July 2007) has the lowest volatility (2.60%) for the entire study period and post-crisis period (August 2007-2010) has the highest volatility (4.11%) for the study period as measured by the standard deviations of weekly returns. Hence, the reforms have made the stock market more stable (therefore less risky for investors) and the crisis has made the stock market more volatile and therefore more risky for investors. Again these conclusions are supported by the low standard deviations in the individual years (2.26%, 3.08% and 2.18% in years 2005-2007) and (4.57% and 5.28% in years 2008 and 2009).

The above facts are illustrated graphically in Figure 5.4 below

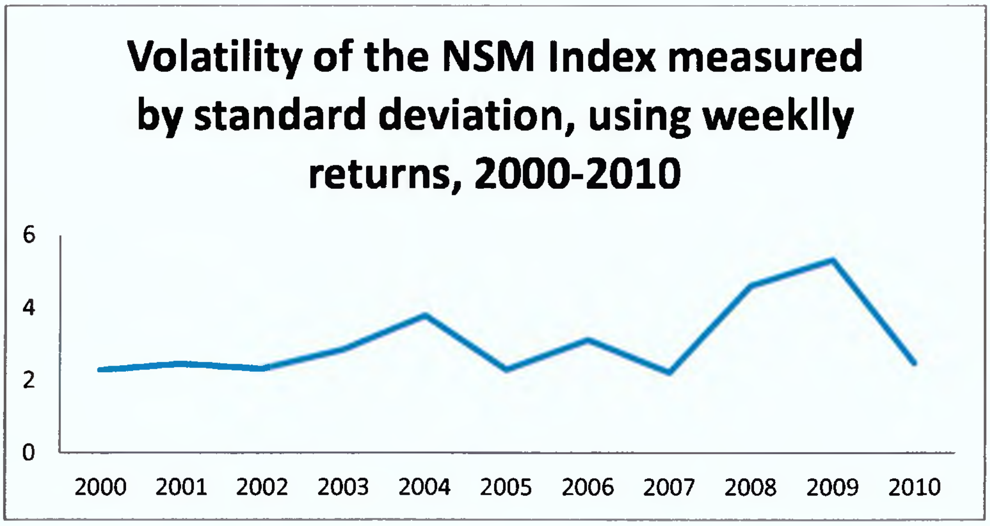


Figure 5-4 : Volatility of the NSM Index measured by standard deviation, 2000 -2010

Different from what we found in the data results for skewness, the table shows that all of the weekly returns are negatively skewed for all the periods of study. However, for the individual years nearly half of the data are positively skewed and the other half are negatively skewed. The kurtosis results show that the distributions are leptokurtic (with kurtosis values much larger than normal kurtosis 3) for all the periods and most of the years. The Jarque-Bera test shows that only four years weekly data are not normally distributed at the 5% level of error (years 2001 and 2004-2006).

However, according to Chen *and* Kuan (2003, p.8), the JB test suffers from size distortion in finite samples. To avoid this problem for monthly data we also used the Shapiro-Wilk W test for normal data. Shapiro-Wilk Test is more appropriate for small sample sizes (< 50 samples) but can also handle sample sizes as large as 2000[21], D'Agostino (1971). The findings shown in table 5.4 confirm the results of JB test.

Table 5-4: Shapiro-Wilk W test for normal data (weekly data)

Variable	Obs	W	V	z	Prob>z
2000-2010	570	0.9541	17.382	6.904	0.0000
2000-2004	257	0.9599	7.456	4.680	0.0000
2005-2010	313	0.9558	9.774	5.362	0.0000
2005-July2007	135	0.89952	10.685	5.341	0.0000
August 2007-2010	178	0.98187	2.444	2.044	0.0205

Table 5-5 Descriptive statistics for monthly return on the NSM all share Index.

Period	Mean	Median	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	Probability
Jan 00 - Dec 10 Overall	1.1833	0.7345	7.6646	-0.6374	8.6538	184.7484	0.0000
Jan 00 - Dec 04 (Pre- Reforms)	2.5396	2.5529	5.5394	-0.1428	3.0649	0.2146	0.8983
Jan 05 - Dec 10 (Post- Reforms)	0.0529	-0.1377	8.9465	-0.4788	7.9139	75.1914	0.0000
Jan 05 - July 07 (Pre- Crises)	2.5779	2.7660	5.4074	0.4179	2.9639	0.9040	0.6364
Aug 07-Dec 10 (Post- Crises)	-1.8562	-1.1867	10.5571	-0.1602	6.7375	24.0387	0.0000
2000	3.7127	3.6916	5.0125	0.2362	2.1473	0.4751	0.7885
2001	2.5109	2.2321	4.1681	0.0568	1.4698	1.1772	0.5551
2002	0.8482	0.4539	3.7024	0.5017	2.3664	0.7041	0.7033
2003	4.2013	3.7887	5.2260	0.3917	2.4765	0.4438	0.8010
2004	1.4257	2.5529	8.4897	-0.2595	1.8933	0.7471	0.6883
2005	0.0839	-0.3653	4.9427	0.1937	1.5811	1.0817	0.5823
2006	2.6717	0.4809	5.7197	1.3391	4.3412	4.4857	0.1062
2007	4.6504	6.1306	4.6874	-0.7096	2.6674	1.0625	0.5879
2008	-5.0987	-5.0379	8.2136	-0.3902	4.5135	1.4497	0.4844
2009	-3.4347	-3.9505	16.1989	0.2128	4.2023	0.8133	0.6659
2010	1.4450	0.6564	5.7238	0.5950	2.4763	0.8451	0.6554

[21] https://statistics.laerd.com/spss-tutorials/testing-for-normality-using-spss-statistics.php

Discussions of results for monthly returns

As expected, the table shows similar finding for the monthly mean returns to the previous outcome of the daily and weekly returns.

Similarly, as measured by the standard deviations of monthly returns, the post-reform/pre-crisis period (2005-July 2007) has the lowest volatility (5.41%) for the entire study period and post-crisis period (August 2007-2010) has the highest volatility (10.56%) for the study period. Hence, the reforms have made the stock market more stable (therefore less risky for investors) and the crisis has made the stock market more volatile and therefore more risky for investors.

The above facts are illustrated graphically in Figure 5.5 below

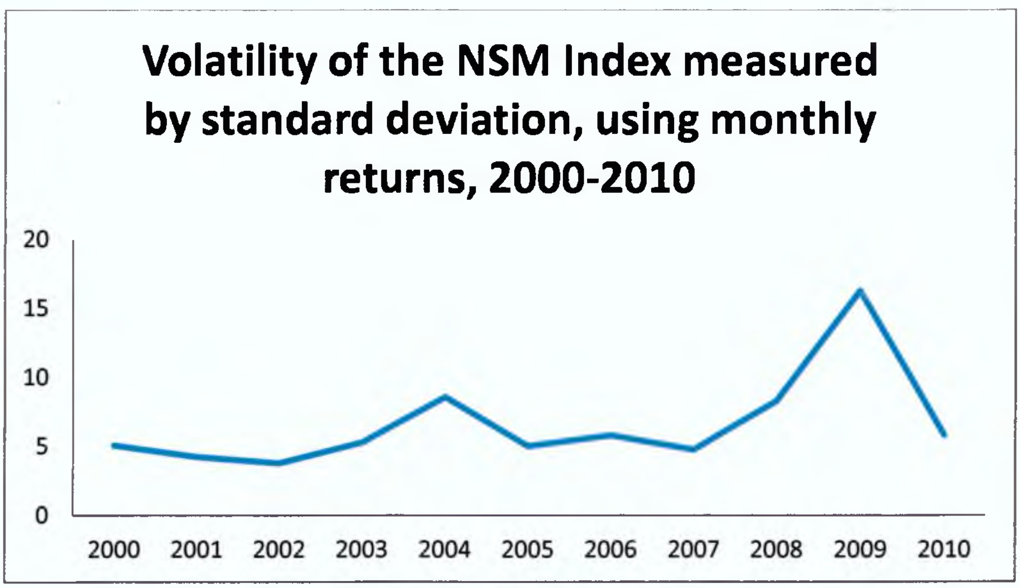


Figure 5-5: Volatility of the NSM Index measured by standard deviation, 2000 -2010

The data results for skewness the table show that all of the Monthly returns are negative skewed for all the periods of study except the post-reform pre-crisis period. However for the individual years all the years are positive skewed except years 2004, 2007 and 2008. The kurtosis results show that the distributions are leptokurtic (with kurtosis values much larger than normal kurtosis 3) for overall, post reforms and post-crises periods and for the years 2006, 2008 and 2009 as well. The Jarque-Bera test shows that all the years monthly data are normally distributed at the 5% level of error, while for the periods, pre-reforms and pre-crises are normally distributed at the same level of error. As mentioned above, the Jarque-Bera test is sensitive to small sample size, thus we run the Shapiro-Wilk W test for normal data as shown in table 5.6. The results again confirm the finding of JB results.

Table 5-6: Shapiro-Wilk W test for normal data (Monthly data)

Variable	Obs	W	V	z	Prob>z
2000-2010	132	0.9197	8.377	4.786	0.0000
2000-2004	60	0.9870	0.708	-0.745	0.7718
2005-2010	72	0.9047	6.003	3.904	0.0001
2005-July2007	31	0.9641	1.169	0.323	0.3734
August 2007-2010	41	0.8997	4.042	2.944	0.0016

It is noteworthy that for fairly large samples (as in the above tables), as a result of the central limit theorem in statistical theory, the JB test has limiting asymptotic distribution which does not unduly distort the performance of the testing procedure, since it remains asymptotically chi-square distributed. Hence, the JB test statistic is robust against the classical assumptions required for testing normality in the case of both daily and monthly returns. This is why in effect the JB test results agree with the Shapiro-Wilks test results in this study.

In summary, the financial reforms have positive overall effect on the NSM and global financial crisis have negative overall effect.

5.4 Univariate Time Series Modelling

A time series is a set of variables with values which represent consecutive measurements taken at equal intervals of time. For examples, the daily, weekly, monthly and yearly stock indexes and returns from the NSM are time series of particular interest in this study. These stock market data are often non-stationary in the sense that they fluctuate wildly from period to period as seen in the above section. According to Islam and Watanapalachaikul (2005, p. 31) time series analysis is the set of statistical methodologies that are appropriate to analyse non-stationary and stationary data series.

Campbell et al (1997) point out that an interesting question in stock market analyses is whether financial asset prices are predictable. The Efficient Market Hypothesis (EMH) provides the view that stock prices cannot be predicted because they vary randomly over time. This behaviour is described as a random walk, $Y_t = Y_{t-1} + \varepsilon_t$ in which current values behave like previous values with random differences between periods.

That is, the concept of random walk in finance implies that changes in stock prices have the same distribution and are independent of each other, such that the share price in the stock market cannot be used to predict future price movements.

In this section we analyse the monthly index and returns data in order to describe further the patterns of stock market activity in the NSM. For example, we describe the trend behaviour of the data using simple and exponential moving averages. These analyses are useful indicators of potential for investors to gain or lose value in their investments in the market, as well as to predict the future values of returns. These advantages of such time series analyses are summarised as follows:

- Use of Double Moving Averages (DMA) and Triple Moving Averages (TMA) signals the periods of upturn and downturn in the NSM. This enables investors to determine when to increase or decrease their investments in the market. This decision will of course require knowledge of the relative performance of stocks in particular sectors of the market, additional to the overall index and returns.
- Use of exponential smoothing models enables investors, policy makers and financial analysts to forecast future values of the index and returns.
- Also, evidence of trends in the returns will support the view that the NSM is not efficient, since the returns do not follow a random walk.

The moving average and exponential smoothing and forecasting models used in this section do not include further explanatory variables apart from the index and returns data for example interest rates, inflation, and price/earnings ratios. The models are therefore univariate time series analyses of the fluctuations of the market index and returns over time. The forecasts of future observations are simply extrapolations of the observed trends in the series to some months in the future. The main features of financial univariate time series data are long-run movements of the series (trends), seasonalities, and cycles. In weekly or monthly data, seasonal component, often referred to as seasonality, is a difference in the time series which depends on the time of the year. It describes any regular fluctuations with a period of less than one year. Islam and Watanapalachaikul (2005) explain that a time series with seasonality can be modelled as a deterministic function of time by including in the regression model a set of n seasonal dummies:

$$D_{it} = \begin{cases} 1 & t \in season(i) \\ 0 & otherwise \end{cases} \quad i = 1,2 \ldots\ldots n \qquad \text{Equation 5-9}$$

where n is the number of seasons in the year for example $n = 4$ for quarterly data, $n = 12$ for monthly data, and so forth. A liner regression model for a time series with a linear trend and seasonal behaviour can be formulated as follows:

$$y_t = \propto + \beta t + \sum_{i=1}^{n} \gamma_i D_{it} + \varepsilon_t \qquad \text{Equation 5-10}$$

where γ_i are the seasonal coefficients which sum to zero.

In the following sub-sections, monthly data for the stock market index and returns from January 2000 to December 2010 are analysed using moving averages, exponential and Holt Winters' smoothing models.

5.4.1 Simple Moving Averages

A simple moving average of ten months is used on the NSM all-shares Index to determine the medium-term trends, smooth the time series and indicate upturns and downturns in the index values. Let MI_t denote the monthly index for the NSM index data. The first10-month moving average (MA) is obtained by adding the index values for months 1-10 and dividing by 10 as follows:

$$MA(10) = \frac{\sum_{t=1}^{10} MI_t}{10} \qquad \text{Equation 5-11}$$

The second10-month MA is obtained by adding the values from months 2-11 and dividing by 10, and so on. Similar calculations are obtained for returns by using monthly returns MR_t in place of the monthly indexes.

Figure 5.6 shows the SMA of 10 consecutive months on NSM index, while Figure 5.7 shows the moving average on the NSM returns. Both figures are computed ten-month moving averages from a series of 10 years starting from January 2000 to December 2010.

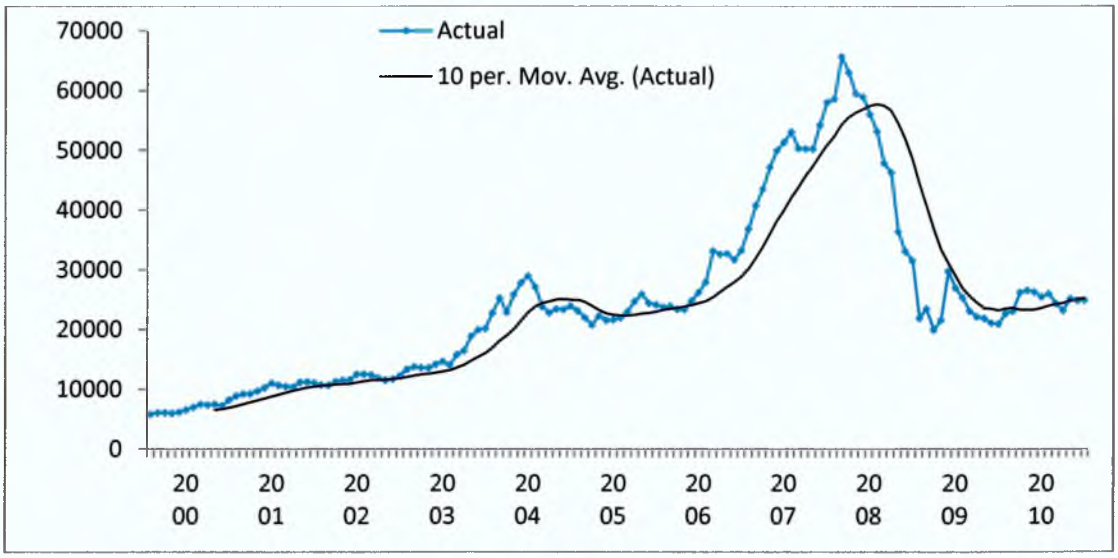


Figure 5-6 : Single moving averages on monthly NSM Index, 2000-2010

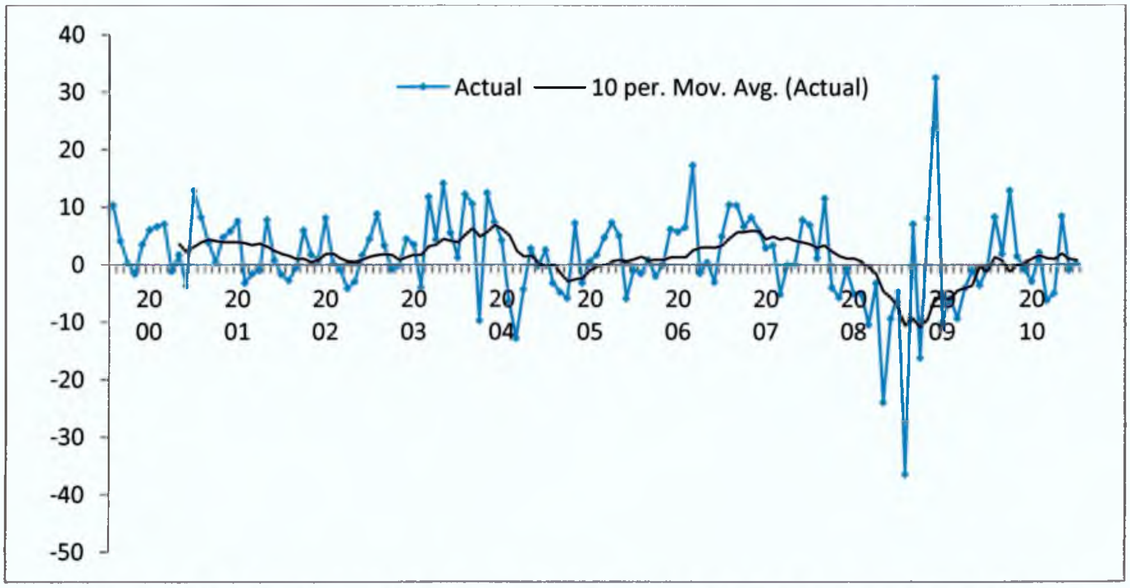


Figure 5-7 : Single moving average on monthly NSM Returns, 2000-2010

Figure 5.6 firstly shows that the index generally increases for the years 2000-2007 and decreases for the years 2008-2009; these results indicate rising and falling market levels, respectively. The 2008-2009 results reflect the negative effect of the global financial crisis on the performance of the NSM.

Secondly, the crossover points between the actual index values and the moving average trend values signal possible positive and negative changes (uptrends or downtrends) in market opportunity, which may also reflect the impacts of financial reforms or the global financial crisis on the NSM. For examples, between 2004 and 2005 the index stays below the trend which shows that a market downturn possibly due to market uncertainties in the first year of the financial reforms; between 2005 and 2007 the index stays above the trend, showing an upturn possibly due to positive impact of the reforms on the NSM. The index stays below the trend again between 2008 to mid-2009 as a result of the negative impact of the financial crisis. A crossover from mid-2009 shows that the index stays above the trend from that point till end of 2010, an indication of recovery from the effects of the crisis and further improvements in the NSM introduced by the Nigerian Stock Exchange (NSE).

Similar interpretations hold for Figure 5.7 for returns. Compared to monthly index, the returns are above or below the MA trend values about equally.

It is explained in the literature that to get better understanding of the above features of time series data using moving averages one needs to plot MAs of different lengths so that both long term movement and short term movement can be seen, Islam and Watanapalachaikul (2005, p. 36).

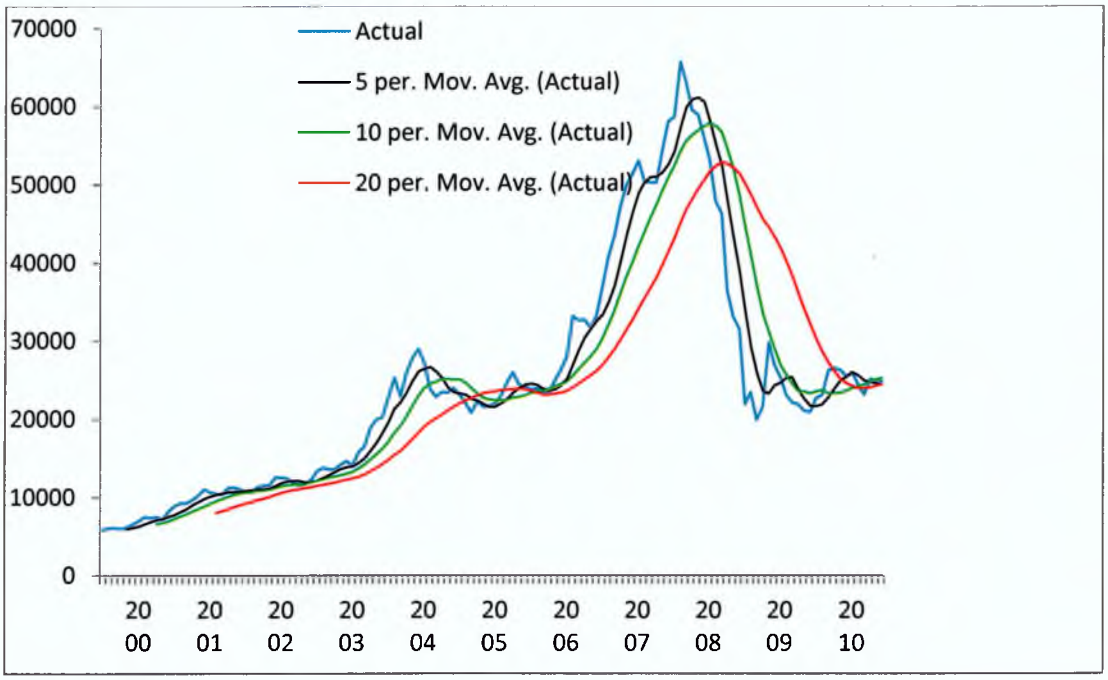


Figure 5-8 : Triple moving averages on monthly NSM Index, 2000-2010

As noted in the above reference a market uptrend is signalled when the 5-point MA stays above the 10-point MA; otherwise a downtrend is signalled. Figure 5.8 shows that crossover points between the 5- and 10-point MAs confirm the above results obtained by comparing the actual index values to the 10-point MA.

5.4.2 Exponential Smoothing Models

Exponential smoothing is a set of methods in time series analysis which generates good prediction as a result of its self-adjusting mechanism for prior errors of forecasting. In addition, exponential smoothing allocates smaller weights to earlier data. The single and double exponential smoothing of the monthly NSM index and returns for overall period (2000-2010) will be discussed in the following sections.

5.4.2.1 Single Exponential Smoothing Model

Single exponential smoothing method is appropriate for series that fluctuate around a constant mean and have neither trend nor seasonal patterns. The smoothed series $\hat{y}_t$ of y_t (Monthly index/returns for NSM) is computed recursively by evaluating:

$$\hat{y}_t = \alpha y_t + (1-\alpha)\hat{y}_{t-1} \qquad \text{Equation 5-12}$$

where $0 < \alpha \leq 1$ is the *smoothing* factor; the smaller the value of α, the smoother the $\hat{y}_t$ series. By repeated substitution, we can rewrite the recursive equation as

$$\hat{y}_t = \alpha \sum_{s=0}^{t-1}(1-\alpha)^s y_{t-s} \qquad \text{Equation 5-13}$$

This shows why this method is called exponential smoothing, the forecast is a weighted average of the past values of y_t, where the weights decline exponentially with time. The forecasts from single smoothing are constant for all future observations. This constant is given by:

$$\hat{y}_{T+k} = \hat{y}_T \qquad for\ all\ k > 0 \qquad \text{Equation 5-14}$$

where *T* is the end of the estimation sample.

However, to start the recursion, we need an initial value for $\hat{y}_t$ and a value for α. In this study we used EViews software to estimate the single exponential smoothing. The software uses the mean of the initial$2/(T+1)$ observations of y_t to start the recursion (where T is the number of observations in the sample) (EViews7.1documentary). Ward (2008) said choice the smoothing parameter is crucial to the behaviour of the forecast series. For sales and business forecasting, values 0.1<α<0.3 have been found to be effective in practice but not optimal. The value could be chosen to minimise some function of the forecast errors, such as mean squared error (MSE) which is the average of the sum of squared forecasting errors. Forecasters normally use the MSE to measure the forecast error.

There are several methods of calculating the MSE at time t. For example,

$$MSE_t = \frac{\sum_{i=l}^{t}(y_i - \hat{y}_i)^2}{t-l} \qquad \text{Equation 5-15}$$

In our study we let EViews estimate α to minimize the sum of squares of one-step forecast errors.

Single exponential smoothing of the NSM Index and return data, 2000 - 2010 have been calculated for the next 50 months with different weight values.

Figure 5.9 shows the forecast of the next 50 months on the NSM index data, 2000 - 2010. The weight value α =0.9998 has been chosen by the software to minimize sum of squared forecast errors, however the result indicate a close match between actual and predicted values as in the figure. In order to determine values of α that will give a closer fit between actual and predicted values, apart from the value chosen by the software, different weight values of 0.2, 0.5 and 0.8 are used in order to characterise the behaviour of the forecast series. The results are presented in Appendixes 5.1 to 5.3 and show that with weight values of 0.5 and 0.8 the actual and predicted value are much closer than when weight value equals 0.2.

Figure 5.10 shows the forecast of the next 50 months on the NSM return data, 2000-2010. The weight value α = 0.1 has been chosen by the software to minimize sum of squared forecast error. The results for values of 0.2, 0.5 and 0.8 show that close match between actual and predicted values appears when the α is close to 1 as can been seen from figures presented in Appendixes 5.4 to 5.6.

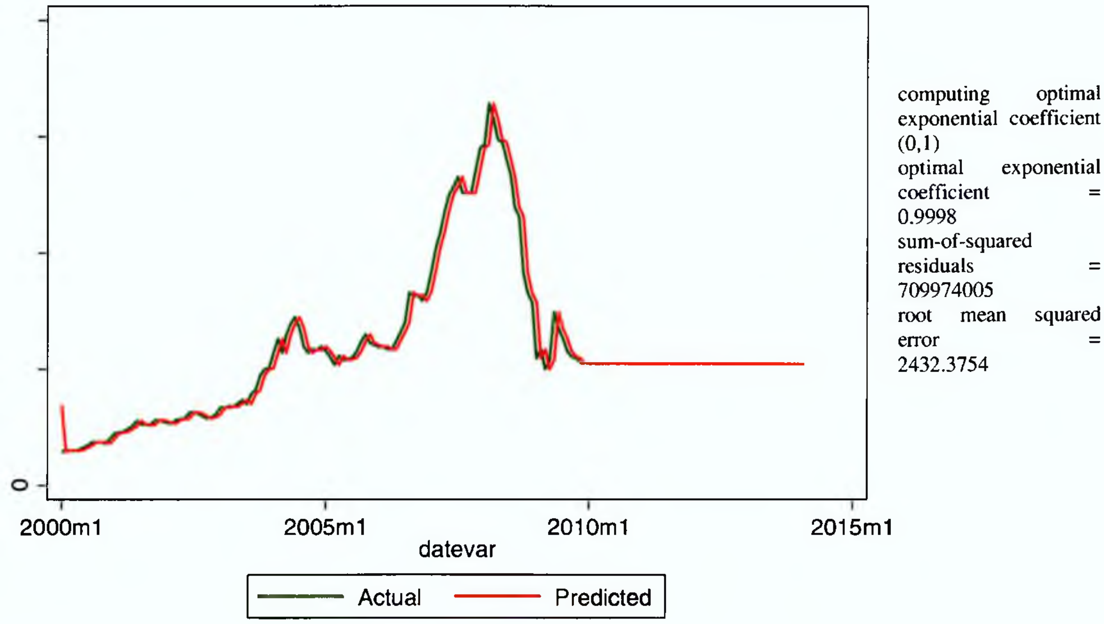


Figure 5-9 : Single exponential smoothing of the NSM Index, α= 0.9998

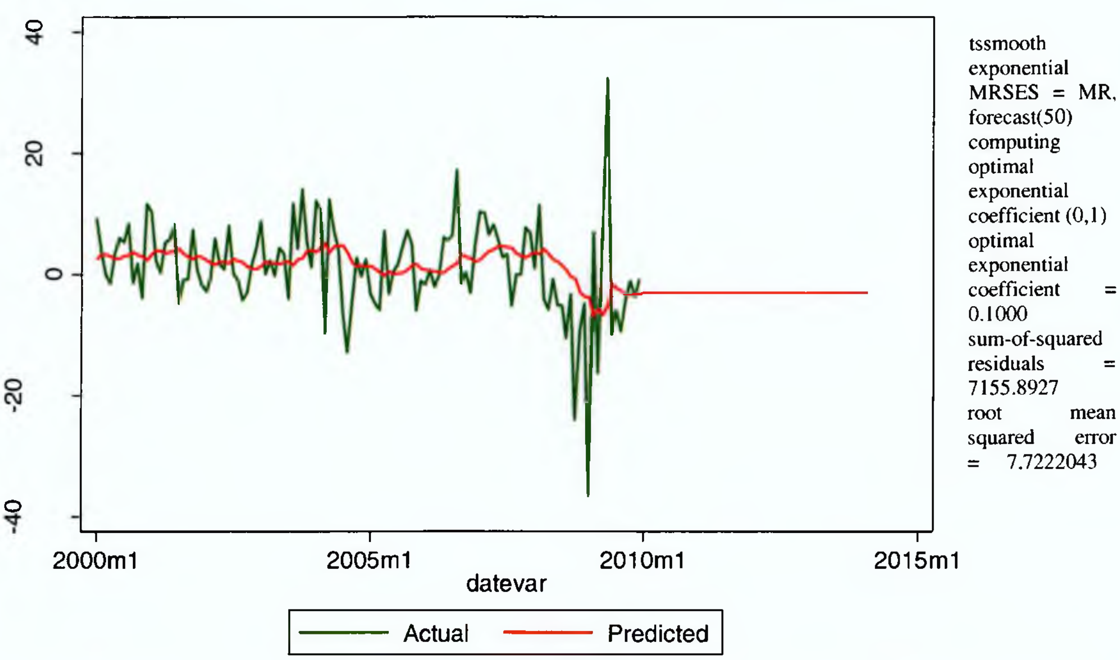


Figure 5-10 : Single exponential smoothing of the NSM Returns, α= 0.1000

Since the forecasts from single smoothing are constant for all future observations with value equal to the last period outcome, the forecasts lag behind the actual data and do not adjust to any trend or seasonality in the series. Therefore, for data that has trend for example NSM index it is preferable to use an exponential smoothing method whose forecasts accommodate trend. The Double exponential smoothing model has this feature and is discussed below.

5.4.2.2 Double (Brown) Exponential Smoothing Model

If a trend or seasonal factors appear in the data, a double exponential smoothing model is applied to the data. A trend can either increase or reduce. A double exponential smoothing considers regression coefficients series that weighted heavier towards latest past. This method applies the single smoothing method twice (using the same parameter) and is appropriate for series with a linear trend. Double smoothing of a series y is defined by (EViews7.1documentary):

$$S_t = \alpha y_t + (1-\alpha)S_{t-1} \qquad \text{Equation 5-16}$$

$$D_t = \alpha S_t + (1-\alpha)D_{t-1} \qquad \text{Equation 5-17}$$

where S is the single smoothed series and D is the double smoothed series. Note that double smoothing is a single parameter smoothing method with damping factor $0 < \alpha \leq 1$.

Forecasts from double smoothing are calculated as:

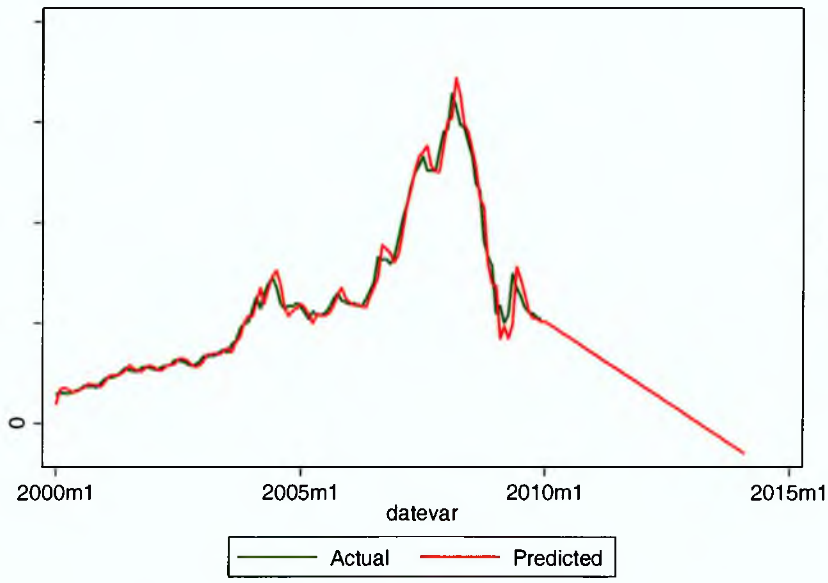
$$\hat{y}_{T+K} = \left(2 + \frac{\alpha k}{1-\alpha}\right) S_T - \left(1 + \frac{\alpha k}{1-\alpha}\right) D_T \qquad \text{Equation 5-18}$$

$$= \left(2S_T - D_T + \frac{\alpha}{1-\alpha}(S_T - D_T)k\right) \qquad \text{Equation 5-19}$$

The last expression shows that when plotted as a function of the period k from end of the data series forecasts from double smoothing lie on a linear trend with intercept $2S_T - D_T$ and slope $\alpha(S_T-D_T)/(1-\alpha)$.

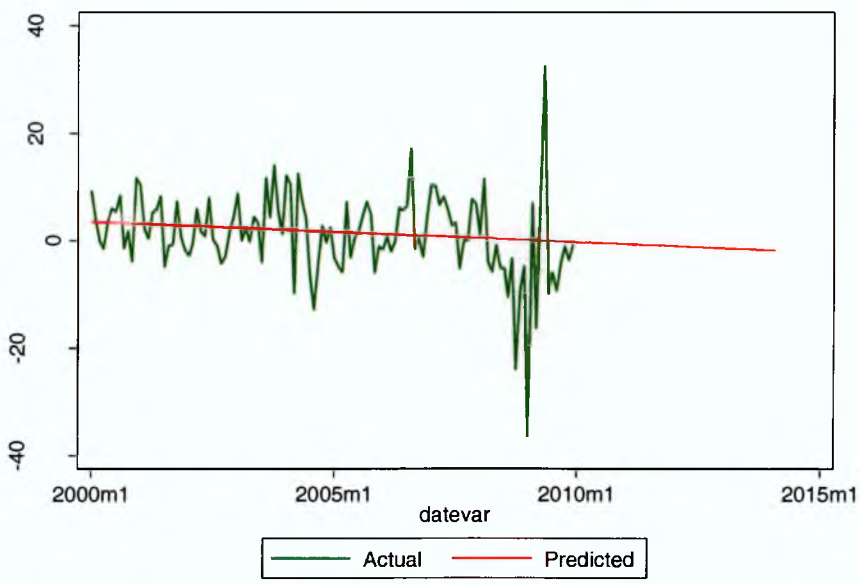
Figure 5.11 presents the forecast for the next 50 months on the NSM Index data, 2000-2010, with different value of an optimal value of $\alpha = 0.6249$ determined by the software. The figure shows a close match between actual and predicted values of the index. Using different values for α as above show similar close matches are obtained for $\alpha = 0.2000$, 0.5000, and 0.8000; see Appendixes 5.7 to 5.9.

On the other hand, Figure 5.12 presents the forecast for the next 50 months on the NSM return data. A smoothing constant of 0.0001 minimizes the root mean squared error. This shows that predicted returns are decreasing with time. The results for other values of α (0.8000 shown in Figure 5.13 below) and (0.2000 and 0.5000) shown in Appendixes 5.10 and 5.11 show closer match between actual and predicted values but the forecasted returns beyond the end of the data series are increasing.



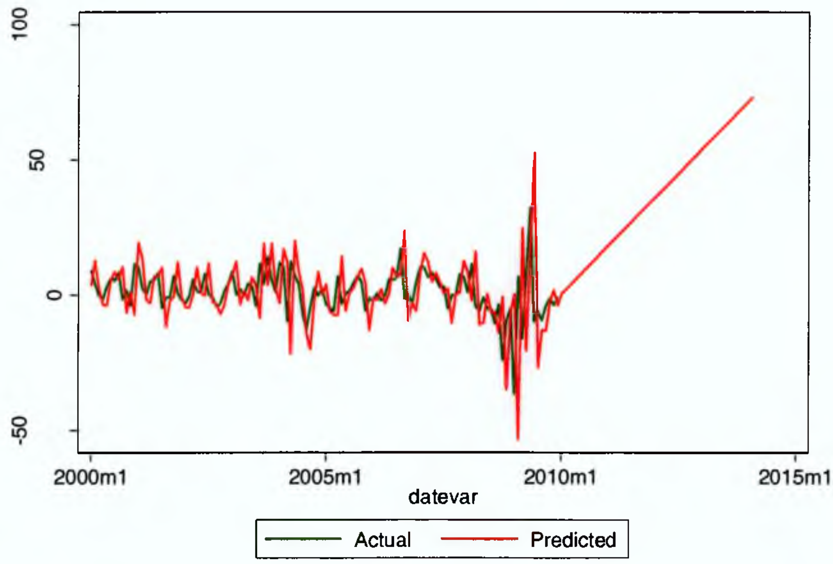
tssmooth dexponential MIDES = MI, forecast(50)
computing optimal double-exponential coefficient (0,1)
optimal double-exponential coefficient = 0.6249
sum-of-squared residuals = 623512862
root mean squared error = 2279.4606

Figure 5-11 : Double exponential smoothing of the NSM Index, α = 0.6249



tssmooth dexponential MRDES = MR, forecast(50)
computing optimal double-exponential coefficient (0,1)
optimal double-exponential coefficient = 0.0001
sum-of-squared residuals = 7025.0273
root mean squared error = 7.6512675

Figure 5-12 : Double exponential smoothing of the NSM returns, α = 0.0001



tssmooth dexponential MRDES8 = MR, parms(0.8) forecast(50)
double-exponential coefficient = 0.8000
sum-of-squared residuals = 22388
root mean squared error = 13.659

Figure 5-13 : Double exponential smoothing of the NSM returns, α = 0.8000

5.4.3 Linear (Holt) Exponential Smoothing Model

This method is appropriate for series with a linear time trend and multiplicative seasonal variation. For the NSM index and returns the wild fluctuations in the series values from month to month suggest evidence of multiplicative effects of time. Particularly for the index data, there is also evidence of trend. Hence, we assume that the Holt-Winters model applies to the data and obtain the following results.

For the 3-parameters Holt-Winters model which accounts for the trend and seasonal effects, the smoothed series $\hat{y}_t$ is given by (as explained by EViews7.1documentary):

$$\hat{y}_{t+k} = (a + bk)c_{t+k} \qquad \text{Equation 5-20}$$

where

a	permanent component (intercept)
b	trend
c_t	multiplicative seasonal factor

These three coefficients are defined by the following:

$$a(t) = \alpha \frac{y_t}{t_t(t-s)} + (1-\alpha)(a(t-1) + b(t-1)) \qquad \text{Equation 5-21}$$

$$b(t) = \beta\big(a(t) - a(t-1)\big) + (1-\beta)b(t-1) \qquad \text{Equation 5-22}$$

$$c_t(t) = \gamma \frac{y_t}{a(t)} + (1-\gamma)c_t(t-s) \qquad \text{Equation 5-23}$$

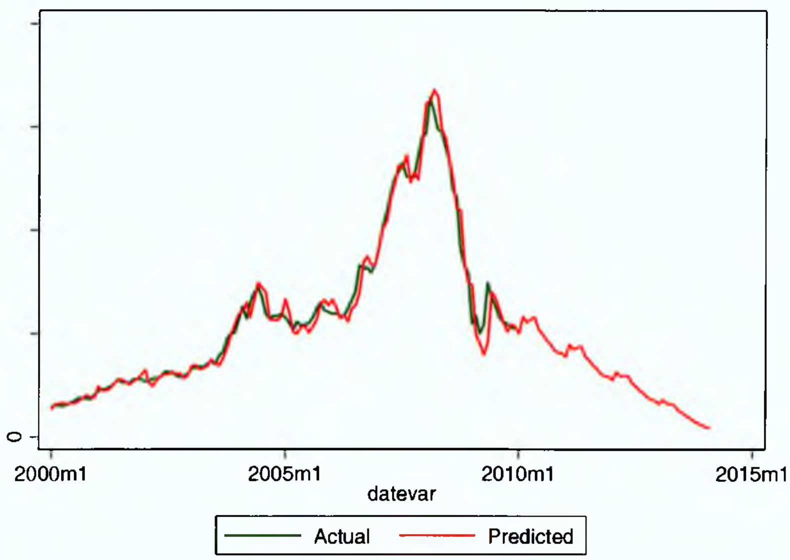
where $0 < \alpha, \beta, \gamma < 1$ are the damping factors and s is the seasonal frequency specified in the Cycle for Seasonal field box.

Forecasts are given by:

$$\hat{y}_{t+k} = (a(T) + b(T)k)c_{t+k-s} \quad \text{Equation 5-24}$$

where the seasonal factors are used from the last s estimates.

The forecast of the NSM Index for the next 50 months are shown in the figures reported in Appendixes 5.12 to 5.15 with different values of weights. The returns on NSM are also presented in Appendixes 5.16 to 5.19 for various weightings as it shown in the figures. The Holt model (α = 0.8200, β=0.3202, γ=1.0000) produces a better forecasting accuracy for the NSM index (Figure 5.14), and the model (α = 0.5000, β =0.5000, γ =0.5000) produces a better forecasting accuracy for NSM returns (Figure 5.15).



Alpha = 0.8200
Beta = 0.3202
Gamma = 1.0000
penalized sum-of-squared residuals = 6.27e+08
sum-of-squared residuals = 6.27e+08
root mean squared error = 2286.722

Figure 5-14 : Holt Winters model of the NSM Index, date 2000-2010

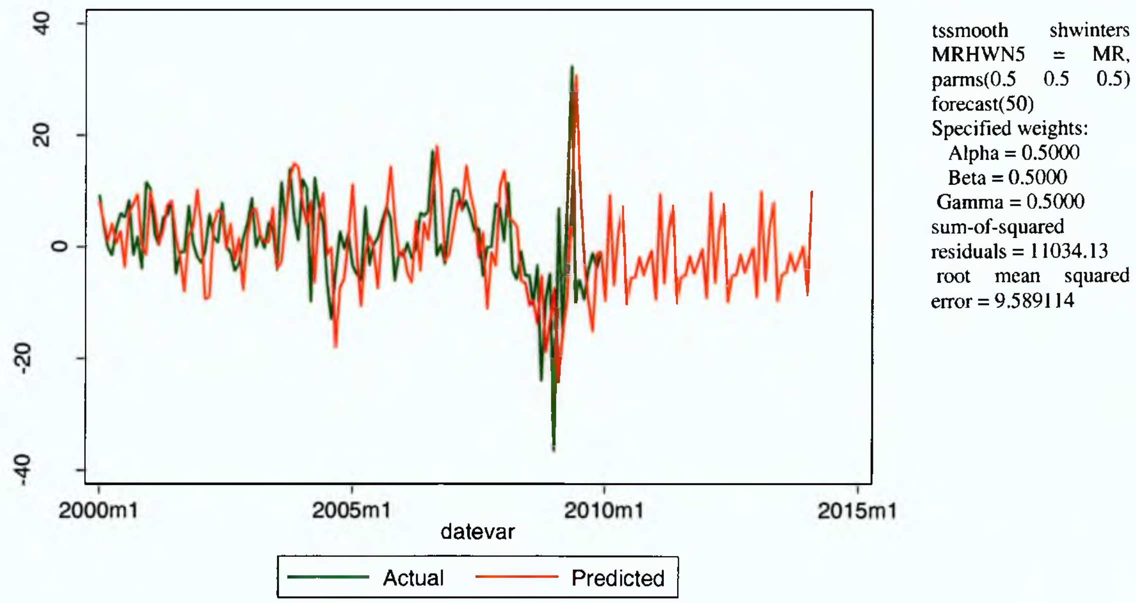


Figure 5-15 : Holt Winters model of the NSM returns, date 2000-2010

In conclusion, exponential smoothing is a technique from several others in time series forecasting models. It is featured by giving heavier weights to latest events and lighter weights to past events. To reduce forecasting error, a chosen optimal smoothing constant (α) is required. The MA and Holt Winters model shows that in the future the NSM Index and Return will have fluctuating trends.

It is noted that the MA models describe the trend behaviour of the data while the exponential smoothing models provide estimated and forecasted values of the index and returns. The single exponential smoothing model gives within- period estimates of the data, but constant forecast values which are all equal to the end of period value. This model is appropriate for the returns data which appear to vary randomly around a constant mean.

The double exponential smoothing model improves these forecasts for trend in the data and the Holt Winters three parameters model improves the forecasts for trend and seasonality effects in the data. Using the different models therefore enables us to explore the NSM index and returns data for different possible characteristics for example trend and seasonality effects, where these effects may be multiplicative as in the Holt-Winters Multiplicative (three parameters) model.

5.5 Summary and Discussion

As initially hypothesised at the beginning of this chapter, the preliminary analyses of NSM data show that the general statistical properties of the NSM are different among the three policy-relevant periods in the study namely the pre-reforms period (2000-2004), the post-reforms/pre-crisis period (2005-July 2007) and post-reforms/post-crisis period (August 2007-December 2010). The key findings are related to the research objectives and questions as follows.

Critical discussion of the results in different periods:

RQ5: How do the results of the research compare for periods before and after the financial reforms and the global financial crisis?

The descriptive statistics of the NSM data presented in Section 5.3 have been used to explore the above research question. The key descriptive statistics for the three periods are recalled from Tables 5.2 to 5.6 as follows:

Table 5-7: Comparative summary statistics for the three periods

		Pre-reforms	Post-reforms/pre-crises	Post-reforms/post-crises
Mean	Daily	0.13	0.13	-0.09
	Weekly	0.58	0.60	-0.42
	Monthly	2.54	2.58	-1.86
Standard Deviations	Daily	1.06	0.84	1.24
	Weekly	2.77	2.60	4.11
	Monthly	5.54	5.41	10.56
Skewness	Daily	0.18	0.14	0.12
	Weekly	-0.20	-0.06	-0.33
	Monthly	-0.14	0.42	-0.16
Kurtosis	Daily	9.14	6.11	3.84
	Weekly	5.63	8.93	3.87
	Monthly	3.06	2.96	6.74
Normality	Daily	not normal	not normal	not normal
	Weekly	not normal	not normal	not normal
	Monthly	normal	normal	not normal

The table shows that:

1. The mean daily, weekly and monthly returns during the pre-reform and post-reform/pre-crisis periods are positive and approximately equal while the mean returns for the post-reforms/post-crisis are negative. Also the highest yearly mean returns are recorded in the post-reform/pre-crisis year 2007. This shows that the reforms may impact the NSM positively, but this impact was limited by the negative effect of the global financial crisis. These statements about possible impacts of the reforms are not statistically confirmed to be the case since the standard deviations for the different periods are different. The possible impacts of both the reforms and global financial crisis are better investigated in the key chapters of the thesis (mainly Chapters 6 and 9).
2. The standard deviations of the daily, weekly and monthly returns in the NSM for the post-reform/pre-crisis period are lower than those for the pre-reform period. Hence, the reforms may have stabilised volatility of NSM returns more than in the pre-reforms period. Compared to the pre-crisis periods, the post-reforms/post-crisis standard deviations are much higher, indicating that the crisis have not only reduced mean returns but also made the NSM much more volatile. For example, the monthly volatility of the post-crisis period is nearly two times that of the post-reforms/pre-crisis period. Again, the remarks in 1) above apply to these notes.
3. The results for skewness, kurtosis and normality show that the NSM returns are generally slightly skewed, leptokurtic and non-normal for daily and weekly data for all the periods. The monthly returns are, however, normal for the pre-crisis periods.

Policy implications of the results

RQ6: What are implications of the research results for investment strategy, stock market development and financial policy in Nigeria?

Result 1 above indicates that the daily returns for NSM only marginally improved following the reforms. There are two possible explanations for this. Firstly, the reforms may have been insufficient thereby failing to generate enough interest from the foreign investors. Foreign investors have a range of options and markets to choose from which means that we are unlikely to witness any significant gains unless the reforms introduced lift the image of NSM to the standard of other emerging markets which the foreign investors can choose to invest in. In the last decade, most of the foreign direct investment (FDI) has gone to the BRIC nations (Brazil, India, Russia and China). With foreign investors finding several interesting and high yield options in other developing nations, NSM may have failed to generate the intended level of interest from these investors, Sanusi (2011), Olaleye (2011).

Secondly, it can be argued that the full impact of the reforms takes some time to take effect. It is found that the reforms took a time lag of 2 years (2004, 2005) to begin to improve the NSM, which experienced only two years of positive effects following the reforms (2006 and 2007), since in mid-2007 the negative effect of the financial crisis manifested in the NSM and globally. The policies that support the reforms need to be maintained to enable the full impact to be realised in the future.

Also the reforms addressed mainly the institutional issues (for example, bank recapitalization) while other important issues such as corruption remained as problematic as before. If the legal and regulatory environments that will make the market players less corrupt and more transparent are not developed as part of the reforms, then firms will not be able to generate attractive returns and with options of other attractive and stable markets such as India and China, foreign investors are less likely to have shown positive reaction to the reforms in the Nigerian market. These could be the reasons why the returns in NSM improved only marginally following the reforms.

The mean returns from the NSM since the outbreak of the subprime crisis have been negative as has been in most of the capital markets around the world. While all of the markets have been affected by the crisis, the extent to which these markets have been affected differ significantly; while some developed countries such as the US have been affected to a great extent, some developing nations such as China and India have managed to survive the recession without much problem.

Returns from NSM were on the lower side of the spectrum in terms of returns. It could be because of the weakness of the domestic market; the countries which managed to survive the subprime crisis are the nations with strong domestic market which managed to keep the industries growing despite the slowdown in the international markets. The countries where the domestic demand declined were the countries which suffered the most during the subprime crisis. Further efforts should be made to deepen the NSM with more financial products so that market activity can include more stocks and related financial products. This will enable investors to have more options for improving investment returns.

The volatility in Nigerian market was mainly because of the volatility in oil prices and demand; funds obtained by selling oil are a major source of investment for the Nigerian government. With high volatility in oil prices, the domestic investment suffered thereby affecting the whole economy. Standard deviation statistics present a similar picture. In the pre reform era the volatility was high and it declined slightly in the post reform (but pre subprime crisis) period. However, the volatility has almost doubled since the outbreak of the subprime crisis. What is interesting to see is that in 2007, the year in which the subprime crisis emerged, the volatility actually declined only to increase to almost double in 2008 and further increasing to double in 2009. Volatility in NSM peaked in 2009. However, year 2010 performance (both in terms of return and volatility) indicates that investor confidence in NSM is returning.

Tables 5.2, 5.3 and 5.5 also indicate that NSM is in high degree of risk due probably to higher degree of speculation over the stocks and consequently generates greater volatility measured by standard deviation as shown in Figures 5.1, 5.2 and 5.3. What is worrying is that higher degree of risk in NSM is not associated with higher returns. Investors who invest in risky stocks do so in order to gain high returns but if the market fails to provide them those high returns, then there is no rationale for these investors to invest in risky stocks. Much of this high degree of uncertainty was due to market inefficiencies which the government tackled through a series of reforms. Since then the risk and return from NSM are proportionate.

Results 3 on the normality tests show that investment returns are non-normal for daily and weekly periods and normal for monthly periods (apart from the post-crisis period). This suggests that investment over longer periods is advisable to minimise risks.

Additional to summary statistics and normality of the returns, the MA modelling results show that between 2004 and 2005 there is a market downturn, as the All Shares Index stays below the MA trend values, possibly due to uncertainties in the first year of reforms. Similarly, there is a market downturn from 2008 to mid-2009 due to the financial crisis and a market upturn from mid-2009 till end of 2010 as a result of recovery from the effects of the crisis and further bank and financial policy reforms following the crisis. These models signal changes in market opportunity which investors and analysts can generally exploit in seeking to improve their returns from the NSM.

The exponential smoothing models show that different types of forecasts of returns and index values can be obtained depending on what assumptions are made about the behaviour of these data. Hence, single exponential smoothing model can be used to obtain non-varying forecasts of returns, while double exponential and Holt Winters models can be used to obtain non-constant forecasts, including those that reflect the presence of trend and seasonal effects in the data. These forecasts will inform the investment decisions of investors in the NSM and determine from the direction of the forecasts whether financial policies which underpin the NSM impact the market positively.

Links to other research questions

The behaviour of NSM data analysed in this chapter shows that there is evidence of excessive volatility in the returns as measured by the standard deviation, especially in the post-crisis period (RQ4).

The returns analysis show that the market may not be efficient since the mean returns are not generally proportionate to the volatilities and the non-normality and high kurtosis properties of the data indicate the presence of asymmetries and imperfections in the market (RQ1). These characteristics are further investigated in subsequent chapters using more powerful models.

5.6 Conclusion

Descriptive statistics and some simple univariate time series models were applied in this chapter in attempt to understand the overall behaviour of the NSM Index and returns during pre-reforms and post-reforms periods (including pre- and post-crisis periods). Various descriptive statistics for daily, weekly and monthly returns were calculated for three time periods namely, overall (2000-2010), pre-reforms (2000-2004) and post-reforms (2005-2010).

The results have been used to explore RQs 5 and 6 which are key aspects of Objective 3 of this research focused on the implications of the findings for investment strategies, stock market development and financial policy.

In conclusion, the time series results in this chapter provide useful information for describing and predicting the behaviour of NSM index and returns. However, the results on skewness and kurtosis indicate some general lack of applicability of the normal distribution which reflects that the NSM is not efficient. These results also have some links with RQs 1 and 4 on market efficiency and volatility in the NSM. For understanding the behaviour of the NSM in depth, it is necessary to focus on specific issues by using more advanced methods and models. The next chapter will focus on discussion of market efficiency.

CHAPTER 6: EFFICIENCY MODELS AND TESTS

6.1 Introduction

This chapter examines the efficiency of the Nigerian Stock Market (NSM) using the returns data described in Chapter 5. The chapter therefore explores the first question of this research:

RQ1 Is the Nigerian Stock Market (NSM) efficient (at least in the weak-form sense of the Efficient Market Hypothesis?)

As explained in chapter 3, in an efficient market asset prices (or returns) reflect available information so that these prices (or returns) measure the true or expected values of the assets. Consequently, when investors trade in stocks in an efficient stock market, based on the stock prices, they are able to allocate their capitals more optimally by investing funds in stocks in proportion to the true values of the stocks. For example, in an inefficient market current prices of some stocks may be much higher than their true values, so that investing more funds in such stocks will eventually reduce future profit, since the funds could not be invested in other stocks that are truly worth more than the chosen stocks. Hence, efficient markets improve the performance of an economy through more effective allocation of investment capital to financial assets.

Different methods for testing efficiency are discussed in the literature and are based on the efficient market hypothesis (EMH). These methods include the runs-test, autocorrelation function test, rational speculative bubbles test, seasonal anomalies test, autoregressive tests, and Brock-Dechert-Scheinman (BDS) test.

This chapter applies some of these tests to the NSM returns data. It also compares the efficiency of NSM before and after 2004 financial reforms introduced by the CBN, by running the tests on the returns data for the entire study period and these two periods.

There are very few studies which test the EMH in African stock markets. One such study was conducted by Olowe (1999) who concluded that NSM exhibits weak form efficiency. However, this finding may not be relevant today since there have been significant developments in the NSM after 1999 for example the 2004 financial reforms and the 2007 global financial crisis. A similar study was conducted by Magnusson and Wydick in (2002). They found that emerging African markets are more weak-form efficient compared to their counterparts in non-African emerging stock markets.

Jefferis and Smith (2005) tested the changing efficiency of African stock markets in the decade ending 2001 using GARCH approach with time-varying parameters. Their findings indicate that there have been changes in weak form efficiency through time in the tested stock markets.

Since most of the empirical work was devoted to the advanced and well-organized stock markets, this study is a contribution to the limited literature on emerging stock markets in Africa and Nigerian stock market in particular. Moreover, the findings of this study would contribute to future research on Nigerian stock market by adding further insight into the dynamics of this market.

6.2 The Theory of Market Efficiency

6.2.1 The Concept of EMH

According to Cuthbertson and Nitzshe (2005, pp. 53-54), stock markets are efficient when asset prices and returns are determined by supply and demand of the assets in a competitive market in which rational traders rapidly use information relevant for the prices and returns to adjust prices. Hence, current stock prices reflect relevant information so that individual agents do not have additional information that will give them comparative advantage over others. In such a market only new information or 'market news' should cause changes in prices or returns. Since 'market news' is unpredictable, price changes (or returns) are unforecastable. In other words, future prices or returns do not depend on previous information; that is, no previous information should help an individual to reduce the forecast error of returns. This independence of forecast errors from previous information is referred to as the *orthogonality property*.

EMH as a concept embodies the above ideas as follows:

1. The fact that stock prices fully reflect available information in a stock market (EMH)
2. The idea that stock prices reflect the true value of the stocks and the true values are given by the expected values; this is the rational expectation (RE) hypothesis in finance theory.
3. The RE hypothesis implies that market participants are rational and profit-maximizing in their investment decisions. Hence, if they have enough information

to understand the true values of the stocks, rational investors will not buy or sell the stocks far above or below the true or expected values. This means that there are no opportunities for abnormal profits in the market.

Let φ_t represent the information available in a market up to time t. A market is efficient in relation to the information set φ_t if it is not possible to make abnormal profits by trading on the basis of φ_t, Cuthbertson and Nitzsche (2005), Jensen (1978).

Equilibrium market price is represented through the Rational Expectations (RE) model of expected returns as:

$$E(P_{i,t+1}|\varphi_t) = [1 + E(r_{i,t+1}|\varphi_t]P_{it} \qquad \text{Equation 6-1}$$

Where E is the expected value operator; P_{it} is the price of security i at time t; $P_{i,t+1}$ is its price at $t+1$; $r_{i,t+1}$ is the one period relative return $(P_{i,t+1} - P_{it})/P_{it}$; φ_t represents the information set up to time t. In case of efficient markets $P_{i,t+1}$ and $r_{i,t+1}$ should be random variables at t.

In case of a "fair game" model this model would mean that the price and return of the security will depend on the information set φ_t which is fully reflected in the stock prices at t, Elton et. al.(2009). But it is difficult to assume that P_{it} is solely dependent on φ_t, especially on that part of φ_t which contains expected returns.

Let $\varepsilon_{i,t+1}$ denote the difference between the actual price of security i at t +1 and the expected price at t + 1 based on the information available to investors at time t. This is also the unexpected or abnormal profit or loss on holding the stock between t and t+1. Thus:

$$\varepsilon_{i,t+1} = P_{i,t+1} - E(P_{i,t+1}|\varphi_t) \qquad \text{Equation 6-2}$$

Under the EMH and as a consequence of the RE hypothesis stated above, investors cannot earn abnormal profits except by chance, so that $E(\varepsilon_{i,t+1}|\varphi_t) = 0$. Equation 6.2 shows that in general the rational expectations model for future returns of stocks can be rewritten as

$$P_{t+1} = E_t P_{t+1} + \varepsilon_{t+1} \qquad \text{Equation 6-3}$$

where P_{t+1} is the future stock price, $E_t P_{t+1}$ is the expected future price given current information and ε_{t+1} is the forecast error. Hence, as in 6.2 above, the forecast error should be zero on average and is independent of (uncorrelated with) any information φ_t available at time t or earlier. This suggests that $\varepsilon_{i,t+1}$ is a "fair game" with respect to the information sequence $\{\varphi\}$.

Similarly, let $\varepsilon_{i,t+1}$ denote the difference between actual and expected returns of security i at $t + 1$. Thus:

$$\varepsilon_{i,t+1} = R_{i,t+1} - E(R_{i,t+1} | \varphi_t) \qquad \text{Equation 6-4}$$

$$\text{Then } E\ (\varepsilon_{i,t+1} | \varphi_t) = 0 \qquad \text{Equation 6-5}$$

This also suggests that $\varepsilon_{i,t+1}$ is a "fair game" with respect to the information sequence $\{\varphi\}$. Hence, the EMH applies to prices and returns; in this chapter we use monthly and daily returns calculated from the All Shares Indexes of the NSM as described in Chapter 5. We further explain below the link between the EMH and random walk behaviour of returns.

6.2.2 The EMH and Random Walk Model of Returns

Random walk models can be categorised on the basis of the dependency between returns r_t and r_{t+k} of two dates t and $t + k$. To do this, define the random variables $f(r_t)$ and $g(r_{t+k})$ while f (.) and g(.) are two arbitrary functions, and consider the situation in which

$$Cov\ [f(r_t), g(r_{t+k})] = 0 \qquad \text{Equation 6-6}$$

for all t and $k \neq 0$. This states that future returns are independent of past returns which is the orthogonality property mentioned above.

The condition of market efficiency is extremely difficult to model mathematically, Fama (1965). The random walk model is one of the few models which allow testing for EMH. Random walk model tests if successive price changes are independent and identically distributed random variables. If this is true then it is not possible to predict future prices using historical data. It is possible to mathematically/statistically test the random walk model which in turn can be used as a test for weak form market efficiency.

If all relevant and available information is fully reflected in stock price, then:

a) In line with equation 6.6 successive price changes will be independent, so that there will be no serial correlation over time between returns;

b) Successive log price changes will be identically distributed:

$$log\ P_{i,t} = log\ P_{i,t-1} + \varepsilon_{i,t} \qquad \text{Equation 6-7}$$

for a particular stock i, where $\varepsilon_{i,t}$ is an identically and independently distributed random variable, that is; a series of identically distributed random variables with zero mean and variance equal to unity.

Using the market index values I_t described in Chapter 5 as measures of overall market prices, we obtain the proportionate returns as

$$R_{t+1} = \frac{I_{t+1} - I_t}{I_t} \approx \ln\left(\frac{I_{t+1}}{I_t}\right) = \ln(I_{t+1}) - \ln(I_t) \qquad \text{Equation 6-8}$$

As stated in equation 6.4, under the EMH, actual returns will sometimes be above and sometimes below expected returns, but on average abnormal returns or the forecast errors $\boldsymbol{\varepsilon}_{t+1}$ is zero. Since future forecast errors are independent of current and past information,

$$R_{t+1} = \varepsilon_{t+1} \text{ or } \ln I_{t+1} = \ln I_t + \varepsilon_{t+1}. \qquad \text{Equation 6-9}$$

This equation states that under the EMH the returns are independently and identically distributed. Equivalently, the natural logarithms of market indexes follow a random walk without drift of the form $Y_{t+1} = Y_t + \varepsilon_{t+1}$, where the error term has zero mean and constant variance. If the returns follow a random walk about a non-zero mean μ, then the natural logarithms of market indexes perform a random walk with drift of the form $Y_{t+1} = \mu + Y_t + \varepsilon_{t+1}$.

The above notes state that in an efficient market the log indexes follow a random walk, so the relative changes in index values defined by the returns are a white noise process. Hence, test of the null hypothesis of market efficiency is formulated as testing the returns for the properties of a white noise process with constant variance as follows:

$$H_0 : E(R_t) = 0;\ \ E(R_t^2) = Var(\varepsilon_t) = \sigma^2;\ \ E(R_t R_s) = 0, \forall t \neq s$$

In other words, test of market efficiency consists in checking whether there are significant autocorrelation of returns at different time points. This test is implemented in this chapter using three approaches, namely: the runs test; autocorrelation function (ACF) test; and the BDS test.

6.3 Brief Review of Key Ideas on the Efficient Market Hypothesis

As discussed above, in an efficient market the path of prices and the return per period are unpredictable. Put more formally, the efficient market hypothesis (EMH) implies that the expected value of tomorrow's price P_{t+1}, given all relevant information up to and including today denoted as φ_t, should equal today's price P_t, possibly up to a deterministic growth component μ (drift). In other words, $E_t\ [P_{t+1} |\ \varphi_t] = P_t + \mu$, where E_t denotes the mathematical expectation operator given the information at time t. In testing the EMH the model commonly used is $P_t = \mu + P_{t-1} + \varepsilon_t$, where $\varepsilon_t \sim$ i.i.d $(0, \sigma^2)$, or returns follow a random walk with drift $\Delta P_t = \mu + \varepsilon_t$. For a long time these models were maintained as an appropriate statistical model of stock market behaviour.

The Efficient Market Hypothesis (EMH) has been the cornerstone of financial research for more than thirty years. The first comprehensive study of the dependence in stock prices can be attributed to Fama (1965) as he analyzed the daily returns of 30 stocks that made up the Dow Jones Industrial average at the time of his study. He found low levels of serial correlation in returns at short lags and provided evidence concerning the non-Gaussian nature of the empirical distribution of the daily returns. He gave two explanations for these departures: the mixture of distributions and changing parameters hypothesis.

The next step in testing the EMH focused on explaining the empirical observation that stock returns are negatively correlated in the long run. For example, the presence of positive feedback traders who buy (sell) when prices rise (fall) causes prices to overreact to fundamentals. However, at some point in time prices start to revert back to their fundamental values, hence we observe mean reversion in returns. This behaviour runs counter to the random walk hypothesis. As shocks are persistent in the case of a random walk, this offers an alternative way to test the EMH, Cuthbertson (1996).

Fama and French (1988) report that price movements for market portfolios of common stocks tend to be at least partially offset over long horizons. They found negative serial correlation in market returns over observational intervals of three to five years. Nevertheless, evidence with respect to the presence of long-term dependence in stock returns is still inconclusive, Poterba and Summers (1988) and Jegadeesh (1990).

It is known that in the short term prices show some form of serial correlation. Empirical evidence confirms that daily prices show some form of dependency/serial correlation (Fama and Blume, 1966, cited in Rubinstein, 2006). But despite these deviations from the strict form of efficient market models, the deviations are not significant enough to declare the market inefficient.

Some researchers investigated the distribution of returns/price changes. It is this distribution which determines the most suitable statistical method for testing the EMH. Bachelier (1900) proposed a model in which he assumed that price changes are normally distributed, Fabozzi (2008). Indeed, the central limit theorem suggests that if the number of transactions is high then we can assume that price changes will be normally distributed. The problem, however, is that in emerging markets such as NSM, the number of transactions may not be that high.

6.3.1 Forms of Efficiency:

Weak-form-efficiency:

Weak-form market efficiency refers to the form of market efficiency in which the stock prices fully reflect only the history of prices. The weak-form efficiency test therefore involves testing the predictability of future returns on the basis of past returns. Fama (1991) expanded the scope of weak-form efficiency tests to include other factors such as earnings to price ratio, dividend yield, etc.

Another key difference in the past tests and the new tests for weak form efficiency is the time horizon used for prediction; while in initial set of tests, the predictability was tested for weekly returns at the maximum, new tests are being used to predict even monthly and annual returns. This has largely been made possible by the invention of powerful computers which can be used to analyse complex relationships using a vast amount of data.

In 1988, Lo and MacKinlay tested autocorrelation in weekly returns of NYSE stocks and concluded that there exists significant and positive autocorrelation in the weekly returns of NYSE stocks. But when they conducted the same tests separately on small and large stocks, they found that the small stocks exhibit stronger correlation in weekly returns compared to large stocks, Taylor (2007).

Conrad and Kaul (1988) also found that weekly returns of small stocks exhibit high degree of autocorrelation as compared to large stocks. Fama (1991) noted that "spurious autocorrelation in portfolio returns, induced by non-synchronous closing trades for securities in the portfolio, is likely to be more important for portfolios titled toward small stocks". This indicates that the effect observed by Lo and MacKinlay (1988a) and Conrad and Kaul (1988) could be because of non-synchronous trading effect.

French and Roll (1986, cited in Cataldo, 2003) found that stock price volatility is higher during trading hours than during non-trading hours. Explaining this they suggest that "most of the volatility in stock prices during trading hours was caused by mis-pricing (4%-12%) but that the principal factor, as suggested by small return variances over exchange holidays and weekends was private information", Cataldo (2003, p63). Thus, the traders who mis-price and buy try to adjust their portfolios by reversing some transactions "which induces negative autocorrelation in daily returns".

The early researchers argued that the autocorrelation although not zero, may not be too distant from zero and hence cannot be used to reject the joint hypothesis of market efficiency and constant expected returns. This view was however challenged by several researchers (for example, Shiller, 1984; Summers, 1986). To prove their point they presented evidence of large slowly decaying swings away from fundamental values (fads, or irrational bubbles), but short-horizon returns have little autocorrelation, Holt and Pressman (2007).

Commenting on Shiller's and Summers' work, Stambaugh (1986) indicates that the large yet temporary deviations from fundamentals imply that long-horizon returns have strong negative autocorrelation and that the variance of returns grow less than in proportion to the return horizon, Holt and Pressman (2007). Also these deviations are temporary and when we look at longer time horizons, the deviations tend to reverse.

The EMH was strongly challenged by DeBondt and Thaler (1985) who provided empirical evidence of instances when the hypothesis fails. For example, they found that stocks that underperform the market in 3-5 year time period tend to follow this underperformance by strong performance. Furthermore they found that it is likely for these stocks to peak in January of year following the last period of their underperformance. Similarly, they found that the stocks which perform better than the market during a 3-5 year period tend to underperform in the following period.

DeBondt and Thaler (1985) explain this using the market overreaction theory. They suggest that markets almost always react to information of higher significance irrespective of whether the information is positive or negative. Thus when the stocks are rising, the investors tend to invest in the stock even beyond its realistic value which eventually constitutes to overreaction. Similarly, when some stocks underperform, their prices continue to decline even after they have already declined to their fundamental value. There, thus, comes a stage where the prices are lower than the fundamental value and at this stage we see a reversal in stock's performance.

Other researchers (Jegadeesh, 1990; Lehmann, 1990 etc.) also found empirical evidence of such reversal of stock prices thereby confirming that markets overreact to both good and bad news.

When we draw a regression graph between the current and historical return data, the slope of the curve represents the autocorrelation. To improve the predictability of the future returns, it is essential to include as many explanatory variables as possible. For example we find that stock market returns are negatively related to interest rates which mean that the interest rates can be one of the variables used to predict future stock prices. Tests indicate that while macroeconomic factors such as inflation and interest rates may not have a great impact on short term stock price movement, they indeed have a significant impact on the long term price volatility.

One of the filters tested by Fama and French (1988) was dividend/price (D/P) ratio. Their analysis indicates that D/P ratio can explain few of the monthly and quarterly return variances. However; if we look at longer time horizons, the explanatory power of the D/P ratio increases. Explaining this Fama and French commented that the change in the explanatory power of D/P ratio over longer time horizon is mainly because of slow mean reversion of expected returns, Lee and Lee (2006).

In a similar study Campbell and Shiller (1988, cited in Taylor and Woodford, 1999) found that the explanatory power of the E/P ratio increases as we increase the time horizon. These studies are quite interesting to understand the implications of slow-moving expected returns for the variation of returns. For example, Fama and French (1988) comment that "if variation in expected returns is common to different securities, then it is probably a rational result of variation in tastes for current versus future consumption or in the investment opportunities" Lee and Lee (2006, p171).

Furthermore, they argue that "there are systematic patterns in the variation of expected returns through time that suggest that it is rational". In addition they report that the variance of expected returns increase from high-grade bonds to low-grade bonds, from bonds to stocks, and from large stocks to small stocks. This result is quite intuitive as low grade bonds, stocks and small stocks are comparatively riskier as compared to high grade bonds, bonds and large stocks.

At the same time Fama and French report that variance in expected returns is almost similar for long term securities such as bonds and stocks indicating that investors allocate equal premium for maturity risks especially for long term securities. Additionally, they also report that variation in expected returns is much higher during periods of slow economic growth as compared to times of booming economic growth. When the slow economic growth lasts longer than investors expect, the perceived risk of investing in risky securities is higher and consequently the expected returns rise further, Lee and Lee (2006).

On the other hand, if the period of low economic growth is short/temporary then the expected returns rise as investors try to increase their present consumption.

Semi-strong-form efficiency (event studies)

Semi strong form of efficiency refers to the form of market efficiency in which the stock prices fully reflect all the *publicly* available information. The tests conducted by Fama (1991) to test semi strong form of efficiency were termed as "event studies". As the name suggests these tests involve studying the stock prices in response to emergence of any news (such as change in corporate structure/firm's financing decision/dividend information/ investment in new projects etc.), Barucci (2003).

In most cases, the event studies involve studying the daily data because the response of the market to any information is expected to be instant. Thus event studies involve linking the release of some information and movement in stock price immediately thereafter. One of the key assumptions of the EMH is that investors react instantaneously to any new information and the semi strong efficient market fulfils this key assumption, Barucci (2003).

However, there are some events for which the market's reaction is spread over a longer time period. For example the announcement of a merger; Investors are often unsure as to how it will impact the merging firm because this impact is dependent on several post-merger variables. In such cases, we may witness a period of instant reaction followed by a long period of volatility as the market tries to adjust to further information regarding the merger (Bruner, 2009). In most cases, the stock price of the acquiring firms decline because investors generally feel that the acquirers pay more than reasonable price for the acquisition and that the success of the merger depends on how the acquiring firm handles the post-merger organisation. Because of the high uncertainty involved, generally the acquiring firms see a decline in stocks post-merger announcement Bruner, (2009).

Summarising the above discussion we can conclude that markets may not always instantaneously react to all the events. But even then in most of the cases, markets do react instantly to the information albeit only to partially reverse the decision later. However, event studies are the best empirical evidence we currently have for studying efficiency and barring a few exceptions event studies support the assumption of market efficiency, Forbes (2009).

Strong-form efficiency

The most rigid form of efficiency is strong-form efficiency. A market is strong form efficient if stock prices fully reflect all the public and private information. In other words, in strong form efficient markets no investors will be able to make abnormal gains using any trading strategy, with luck being the only exception. It is extremely difficult to test for strong form efficiency because the inside/private information used is not publicly known and cannot be properly tested, Madura (2008).

Some analysts have may have access to other information which they can use to make abnormal gains. Similarly, some corporate insiders may have information which can be used to make abnormal gains. This, however, is deemed illegal under the modern financial market laws and people using insider information to make inappropriate gains may be subject to criminal investigation. Regulatory bodies such as the US Securities and Exchange Commission have developed strict rules to prevent insider trading, Ross et al (2008).

In this research we do not have stock-level data on prices and returns. We limit our analysis to past data on overall market returns so that our test of efficiency of the NSM as a whole is related to weak-form efficiency.

6.4 Market Efficiency Models and Tests

Several econometric techniques have been developed to test for efficiency based on the random walk model. In this section we discuss the methods which will be used to examine the efficiency of Nigerian Stock Market.

6.4.1 Runs test

Runs test is commonly used to test for random walk feature in a set of data. In a runs test we calculate the number of sequences of consecutive positive and negative returns. These sequences are known as runs. Consider for example a particular sequence 10100110011 where 0 represents a negative return while 1 represents a positive return. It contains 4 runs of 1 (of lengths 1,1 2 and 2) and three runs of 0 (of lengths 1, 2 and 2). In total this sequence has 7 runs. This number of runs can be compared with expected number runs under the random walk hypothesis of independence of successive returns (also the EMH which it supports), to see if the observed returns follow a random walk.

According to Simons and Laryea (2006, p560) "*the runs test can be used to examine the serial independence in share return movements. This test has the advantage of ignoring the distribution of the data, and does not require normality or constant variance of the data*".

To ensure that equal weight is assigned to all types of run, runs were marked with a + for positive run, with - for negative run and with 0 for no change. Actual number of runs (*R*) was then compared with expected number of runs (*m*) which is estimated using the equation below:

$$m = \frac{[N(N+1) - \sum_{i=1}^{3} n_i^2]}{N} \qquad \text{Equation 6-10}$$

where N is the total number of runs of all types and n_i is the number of runs of type i in each category (+, - and 0). When N exceeds 30, m approximately corresponds to a normal distribution with a standard deviation (σ_m) specified in equation below.

$$\sigma_m^2 = {[\sum_{i=1}^{3}\{\sum_{i=1}^{3} n_i^2 + N(N+1)\} - 2N(\sum_{i=1}^{3} n_i^3 - N^3)]}\Big/{N^2(N-1)} \quad \text{Equation 6-11}$$

Following this, we can test for serial dependence of points in the data set by comparing the observed number of runs R to the expected number of runs given serial independence. The null hypothesis is

$$H_0 : E(runs) = m,$$

and the test statistic is the standard normal Z-statistic ($Z \equiv (R-m)/\sigma_m$).

6.4.2 Autocorrelation Function Test

The correlation between the current return R_t and the return separated by k lags R_{t-k} is measured by the autocorrelation coefficient ρ_k, which can be calculated by the covariance ratio between R_t and R_{t-k} to the product of their standard deviations as follow:

$$\rho_k = \frac{cov(R_t, R_{t-k})}{\sigma(R_t)\sigma(R_{t-k})} \quad \text{Equation 6-12}$$

There will be no serial dependence, if the returns trace a random walk (that is, if the market is at least weak-form efficient); however, if a serial correlation exists in the returns, this contradicts the market efficiency hypothesis, since the information of past stock returns are capable to describe a major amount of the variation in stock returns. It also implies a predictability power of past stock returns in forecasting future returns. The autocorrelation coefficients will not be significantly different from zero under the null of random walk. The sample autocorrelation coefficient at lag k can be calculated by:

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k}(R_t - \bar{R})(R_{t+k} - \bar{R})}{\sum_{t=1}^{n}(R_t - \bar{R})^2} \quad \text{Equation 6-13}$$

where k is the number of lags, and R_t represents the real rate of return calculated as:

$$R_t = \ln(\frac{I_t}{I_{t-1}}) \times 100 \quad \text{Equation 6-14}$$

I_t stock market index at time t, $\bar{R}$ is the sample mean of returns.

In this research ρ_k is calculated for ρ_1 up to ρ_{10}. Therefore the hypothesis to be tested is

$H_0 : \rho_k = 0$ (NSM is weak-form efficient) versus

$H1: \rho_k \neq 0$ (NSM is not weak-form efficient).

If the serial correlation coefficients are significantly different from zero, then we reject the hypothesis that changes in prices or returns follow a *random walk*. The test is conducted at 5% level of significance.

6.4.3 Ljung-Box Q-statistics (Box - Pierce Q (BPQ) test)

Box-Pierce Q test is a portmanteau test that studies the overall randomness of data based on chosen lags. In other words, the test is employed to examine a set of k serial correlation coefficients simultaneously for a hypothesis of no serial correlations up to k lags. Hence, it examines the following joint null hypothesis:

$$\rho_1 = \rho_2 = \cdots = \rho_k = 0$$

The Box-Pierce statistic can be estimated by:

$$QLB_k = N(N+2)\sum_{t=1}^{k}\frac{\hat{\rho}_t^2}{t} \qquad \text{Equation 6-15}$$

where $\hat{\rho}_t$ is the sample autocorrelation coefficient at lag t, N is the total number of observations.

6.4.4 BDS (Brock-Dechert-Scheinkman) test for independence of returns

Typically, in financial markets the lack of independence and equality in distributions of successive outcomes may be due to nonlinearities in the market. Residuals in linear models which has a random walk feature despite being i.i.d. can still exhibit some form of nonlinear (chaotic) dependence. This implies that the random walk model may miss-specify the stochastic process which underpins the dynamics of NSM returns, and thereby distort the asymptotic normal distribution of the usual test statistics employed in normality tests. The BDS test, Brock et al. (1991) as a test of i.i.d. behaviour of model residuals is robust against nonlinearities in the data generating process. The BDS test statistic is implemented as follows.

We first select a value of m (embedding dimension) embed the time series into m-dimensional vectors by taking each m successive points in the series. This results in a conversion of a series of scalars into a series of vectors:

$$x_{N-m}^{m} = (x_{N-m}, x_{N-m+1} \cdots \cdots x_N)$$

Next we compute the correlation integral which measures the spatial correlation among points. This is done by counting the proportion of points in m-dimensional hyperspace that are within a radius ε of each other:

$$C_{\varepsilon,m} = \frac{1}{N_m(N_m-1)} \sum_{i<a} I_\varepsilon(x_i^m, x_j^m) \qquad \text{Equation 6-16}$$

where I_ε is an indicator function that equals one if $\|x_i^m - x_j^m\| < \varepsilon$ and zero otherwise. If the time series is i.i.d. then

$$C_{\varepsilon,m} \approx [C_{\varepsilon,1}]^m$$

If N/m >200 and $0.5 \leq (\varepsilon/\sigma) \leq 2$ (Lin, 1997) and $2 \leq m \leq 5$ (Brock et. al., 1987) then the quantity $[C_{\varepsilon,m} - (C_{\varepsilon,1})^m]$ has an asymptotic normal distribution with mean 0 and variance $V_{\varepsilon,m}$ given by

$$V_{\varepsilon,m} = 4[K^m + 2\sum_{j=1}^{m-1} K^{m-j}C_\varepsilon^{2j} + (m-1)^2C_\varepsilon^{2m} - m^2KC_\varepsilon^{2m-2}]$$

where

$$K = K_\varepsilon = \frac{6}{N_m(N_m-1)(N_m-2)} \sum_{i<j<N} h_{i,j,N;\varepsilon}$$

and

$$h_{i.j,N;\varepsilon} = \frac{[I_{i,j;\varepsilon}I_{j,N;\varepsilon} + I_{i,N;\varepsilon}I_{N,j;\varepsilon} + I_{j,i;\varepsilon}I_{i,N;\varepsilon}]}{3}$$

The BDS test statistic, which has a limiting standard normal distribution, is given by:

$$BDS_{\varepsilon,m} = \frac{\sqrt{N}[C_{\varepsilon,m} - (C_{\varepsilon,1})^m]}{\sqrt{V_{\varepsilon,m}}} \qquad \text{Equation 6-17}$$

Since the BDS test is a two tailed test we will reject the null hypothesis if $BDS_{\varepsilon,m}$ does not lie between the critical values. The value of ε should be set to between half and three halves the standard deviation of the actual data and m should be set in line with the number of observations available, Brock et al. (1991).

6.5 The Data

In this chapter NSM all share indexes' daily and monthly all share index data are used to calculate the continuously compounded returns used in this analysis. For each series, the daily and monthly return (R_t) of the Nigerian stock market composite index will be calculated according to the following equation:

$$R_t = \ln\left({}^{I_t}/_{I_{t-1}}\right) \times 100 \qquad \text{Equation 6-18}$$

where I_t is the stock index closing price on time (day/month) t, and I_{t-1} is the stock index closing price on the previous trading time.

As mentioned earlier in Chapter 5, the data covers the period from 1 January 2000 to end of December 2010. The data analysis is carried out on three levels: first overall period that covers the period from 1 January 2000 to end of December 2010; second, the period duration between January 2000 till end of December 2004 which is named the pre-reforms period; then the period from 1 January 2005 to end of December 2010 which is named the post-reforms period. The aim of the three levels of data examination is to investigate the influence of the financial reforms on NSM.

6.5.1 Normality and Stationarity of NSM Returns

Before applying the market efficiency test, each series will be tested for a unit root. It is very important to test the data series for stationarity. This test can be carried out by employing unit root tests to assure the stationarity of the underlying variables and avoid any possible spurious regression that may be involved in the serial dependence test. A time series is stationary if its mean and variance are constant over time. Therefore, stationarity tests will be performed using two of the well-known test in the literature namely, the Dickey-Fuller (DF) and Philips-Perron (PP) tests. The null hypothesis in DF and PP tests is that a series has a unit root, which means a stationary series should have significant DF and PP statistics.

Dickey-Fuller Test:

If a series has a unit root, then the series is non-stationary and the standard least squares estimator is not normally spread. Dickey and Fuller (1979) have studied the limitation of distribution in standard least squares estimator of autoregressive models for the time series with a simple unit root. Dickey, Hasza, and Fuller (1984) gained the limiting distribution for a time series that has seasonal unit roots.
Suppose that AR(p) model is given by:

$$Y_t = \alpha_1 Y_{t-1} + \cdots + \alpha_P Y_{t-P} + \varepsilon_t, \quad t = 1,2,\ldots,T \qquad \text{Equation 6-19}$$

where $\alpha_1, \alpha_2, \ldots, \alpha_P$ are constants and ε_t is a white noise series with a zero mean and variance of σ_ε^2.
If all of the characteristic roots of $X^P - \alpha_1 X^{P-1} - \cdots - \alpha_P = 0$ are smaller than one in absolute value, then $Y_t \sim AR(P)$ is stationary. If there is a unit root then $Y_t \sim AR(P)$ is

non-stationary and the summation of autoregressive parameters calculated by $\sum_{i=1}^{p} \alpha_i$ in equation (6.19) is equal to 1. As a result, the unit root property is tested by using the hypothesis $H_0: \sum_{i=1}^{p} \alpha_i = 1$ against $H_1: \sum_{i=1}^{p} \alpha_i \neq 1$. Dickey-Fuller test is used to examine the null hypothesis that the time series shows a lag-d unit root (hence non-stationary) against the alternative of no unit root.

Phillips-Perron Test

The Phillips-Perron is another statistical test for stationarity or unit roots. It carries out tests for zero mean as well as non-zero mean in an autoregressive model. A zero-mean autoregressive model is represented by

$$Y_t = \alpha Y_{t-1} + \varepsilon_t \qquad \text{Equation 6-20}$$

and a non-zero-mean model is given by

$$Y_t = \mu + \alpha Y_{t-1} + \varepsilon_t \qquad \text{Equation 6-21}$$

where $\varepsilon_t \sim$ serially correlated.

The Phillips-Perron test is for a null hypothesis that Y_t has a unit root ($H_0 : \alpha = 1$), that is returns are non-stationary, against a stationary alternative ($H_1 : \alpha \neq 1$). Philips-Perron tests and Dickey-Fuller tests are alike, except that Philips-Perron test adds an automatic correction to Dickey-Fuller test procedure to permit auto-correlated residuals. In addition, Philips-Perron test's errors are identically and independently distributed.

Remarks

In order to represent the data generating process for a time series, one may include or not include constants and time trends in the time-series model without testing for these features, if it is assumed that that these are part of the data generating process. Although introducing such additional nuisance parameters in a broad model specification increases the size of the critical region, the conclusions are sufficiently robust irrespective of the particular specification, especially in a study such as this in which the emphasis of the modelling process is not the modelling diagnostics, but the use of the modelling results in describing different behaviours of the time series within or outside those covered by financial reforms and global financial crisis.

6.6 Empirical Results

Table 6.1 shows the unit root tests for Nigerian Stock Market returns. As explained above, the null hypothesis in Dickey-Fuller and Phillips-Perron tests is that a series has a unit root, which means a stationary series should have significant Dickey-Fuller and Phillips-Perron statistics. The tests were conducted on the first log difference of the stock market returns for each time periods of the study. These tests were applied with constant term and no time trend. The Dickey-Fuller and Phillips-Perron test results show strong evidence that the return series for the three study periods are stationary at 1%, 5% and 10% significance levels.

Table 6-1: Unit root tests[22] for Nigerian Stock Market returns

Series of returns	Dickey and Fuller (DF)		Phillips-Perron (PP)	
	Daily	Monthly	Daily	Monthly
Over All	-25.692*	-9.671*	-29.713*	-9.671*
Pre-reforms	-18.253*	-6.594*	-23.151*	-6.552*
Post-reforms	-18.806*	-7.199*	-19.735*	-7.400*

Serial correlation tests are based on the assumption that stock market returns are normally distributed, therefore it is important to check whether the data series approximates a normal distribution. The results for normality test for the three periods under the study are reported in Tables 6.2 and 6.3.

Table 6-2 Normality tests for daily NSM Returns

Series of returns	Observations	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Brea	Probability
Over All	2592	0.0599	1.0713	-0.0193	6.399	1248.559	0.0000
Pre-reforms	1130	0.1341	1.0388	-0.0623	9.3253	1884.504	0.0000
Post-reforms	1462	0.0026	1.0926	0.0240	4.5857	153.3081	0.0000

Source: Calculated using Eviews 7

[22] Note:

- For over all daily series, the 1%, 5% and 10% critical values are -3.430, -2.860, -2.570 for DF, -3.430, -2.860, -2.570 for PP, respectively. For over all Monthly, the 1%, 5% and 10% critical values are -3.500, -2.888, -2.578 for DF, -3.500, -2.888, -2.578 for PP respectively.
- For pre-reforms daily series, the 1%, 5% and 10% critical values are -3.430, -2.860, -2.570 for DF, -3.430, -2.860, -2.570 for PP respectively. For pre-reforms monthly, the 1%, 5% and 10% critical values are -3.569, -2.924, -2.597 for DF, -3.567, -2.923, -2.596 for PP respectively.
- For post-reforms daily series, the 1%, 5% and 10% critical values are -3.430, -2.860, -2.570 for DF, -3.430, -2.860, -2.570 for PP, respectively. For post-reforms Monthly, the 1%, 5% and 10% critical values are -3.552, -2.914, -2.592 for DF, -3.551, -2.913, -2.592for PP respectively. *, ** and *** denotes the rejection of the null hypnotises at 1%, 5% and 10% respectively.

These calculation done by STATA SE 11.0

Table 6-3 Normality tests for Monthly NSM Returns

Series of returns	Observations	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Brea	Probability
Over All	132	1.1833	7.6646	-0.6374	8.6538	184.7484	0.0000
Pre-reforms	60	2.5400	5.5394	-0.1428	3.0648	0.2146	0.8983
Post-reforms	72	0.0529	8.9465	-0.4788	7.9139	75.1914	0.0000

Source: Calculated using Eviews 7

For the daily stock returns all periods had a skewness value of less than 0.1 and none of them have a kurtosis less than four; therefore, they were all leptokurtic. The three periods had of 0.0000 of P-value, thus, the normality assumption was rejected for all periods of the study. Table 6.3 shows same result for monthly data for both overall and post-reforms periods, where for pre-reforms period different results can be seen. The kurtosis for this period equal to 3.0648 which indicate that the monthly data during pre-reforms period was not leptokurtic, furthermore the p-value of this period is 0.8983 and there Jarque-Brea is 0.2146, thus the normality assumption was accepted for this period. Generally speaking it can be concluded that the NSM return data does not follow normal distribution. This result is also confirmed by the Shapiro-Wilk W test for normal data in Chapter 5 of the thesis.

The above fact of non-normality of returns is supported by most of the studies on emerging markets such as Bekaert and Harvey (2002), Mlambo et al. (2003), Poshakwale (1996), Marashdeh and Shrestha (2008) and Al-Khazali (2007) which also conclude that emerging market returns are not normally distributed.

However, Mlambo et al. (2003, p 28) suggests that if there is a strong deviation from normality, the correlation analysis should be done using nonparametric testing method, such as run test, since they do not assume a specific distribution. Nevertheless, he conducted parametric serial correlation tests even though the normality assumption had been rejected. His justification is that these tests "help in detecting the presence of higher order serial correlation which is difficult to detect by merely using the runs tests". For this reason both parametric (Autocorrelation Coefficients and Q-statistics) and nonparametric (Run tests and BDS) tests are conducted in this study.

6.6.1 Autocorrelation Coefficients and Q-Statistics

Autocorrelation coefficients, Partial Correlation coefficients and Q-Statistics for the NSM market are reported in Tables 6.4 to 6.9 for the first 10 lags. For the daily data for the three periods of study, the results indicate a strong evidence of negative first-order correlation where the null of no first-order serial dependence was rejected for NSM market in all the three periods. The ACF statistics suggest a strong evidence of serial correlation in the first 10 lags for NSM; the autocorrelation coefficients are significant at the one percent level, the results of autocorrelation test in Table 6.4, 6.5 and 6.6 indicate a strong evidence of serial correlation in the NSM daily stock returns.

Table 6-4 Autocorrelation Coefficients and Q-Statistics for daily data (2000-2010)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.251	-0.251	163.76	0.000
		2	-0.070	-0.142	176.32	0.000
		3	-0.088	-0.157	196.64	0.000
		4	-0.080	-0.179	213.34	0.000
		5	-0.026	-0.152	215.07	0.000
		6	0.010	-0.113	215.34	0.000
		7	-0.036	-0.150	218.64	0.000
		8	0.020	-0.114	219.70	0.000
		9	0.019	-0.089	220.65	0.000
		10	0.004	-0.087	220.69	0.000

Source: Calculated using Eviews 7

Table 6-5 Autocorrelation Coefficients and Q-Statistics for daily data (2000-2004)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.351	-0.351	139.73	0.000
		2	-0.045	-0.193	142.07	0.000
		3	-0.008	-0.113	142.15	0.000
		4	-0.086	-0.168	150.56	0.000
		5	-0.037	-0.181	152.08	0.000
		6	-0.008	-0.166	152.16	0.000
		7	-0.023	-0.179	152.76	0.000
		8	0.053	-0.112	155.99	0.000
		9	0.024	-0.078	156.67	0.000
		10	0.015	-0.055	156.91	0.000

Source: Calculated using Eviews 7

Table 6-6 Autocorrelation Coefficients and Q-Statistics for daily data (2005-2010)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.140	-0.140	28.873	0.000
		2	-0.096	-0.118	42.497	0.000
		3	-0.175	-0.214	87.357	0.000
		4	-0.072	-0.161	94.975	0.000
		5	-0.017	-0.122	95.389	0.000
		6	0.032	-0.077	96.927	0.000
		7	-0.052	-0.146	100.97	0.000
		8	-0.014	-0.121	101.27	0.000
		9	0.013	-0.085	101.53	0.000
		10	-0.008	-0.111	101.62	0.000

Source: Calculated using Eviews 7

This conclusion can be supported by the Ljung-Box Q statistics for the first ten lags where the null hypothesis is rejected at even one percent for all periods under study. As a result, one can strongly reject the null of no serial correlation in NSM returns.

Tables 6.7, 6.8 and 6.9 represent same results for the monthly data for the three periods of study, a strong evidence of negative first-order correlation where the null of no first-order serial dependence was rejected for NSM market in all the three periods at 10% significant level. In addition the ACF statistics suggest a strong evidence of serial correlation in the first 10 lags for NSM; the autocorrelation coefficients are significant at the ten percent level, the results of autocorrelation test indicate a strong evidence of serial correlation in the NSM monthly stock returns. This result also supported by Q-statistics test.

Table 6-7Autocorrelation Coefficients and Q-Statistics for monthly data (2000-2010)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.499	-0.499	33.434	0.000
		2	0.013	-0.315	33.458	0.000
		3	0.144	-0.007	36.268	0.000
		4	-0.334	-0.353	51.611	0.000
		5	0.271	-0.104	61.772	0.000
		6	-0.069	-0.065	62.441	0.000
		7	-0.107	-0.157	64.049	0.000
		8	0.122	-0.174	66.152	0.000
		9	-0.084	-0.114	67.153	0.000
		10	0.134	0.069	69.733	0.000

Source: Calculated using EViews 7

Table 6-8 Autocorrelation Coefficients and Q-Statistics for monthly data (2000-2004)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.367	-0.367	8.3378	0.004
		2	-0.091	-0.260	8.8558	0.012
		3	-0.107	-0.303	9.5932	0.022
		4	0.015	-0.258	9.6089	0.048
		5	0.105	-0.108	10.347	0.066
		6	0.073	0.040	10.707	0.098
		7	-0.306	-0.327	17.191	0.016
		8	0.291	0.074	23.175	0.003
		9	-0.075	0.014	23.586	0.005
		10	-0.005	-0.038	23.587	0.009

Source: Calculated using Eviews 7

Table 6-9 Autocorrelation Coefficients and Q-Statistics for monthly data (2005-2010)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.542	-0.542	21.726	0.000
		2	0.044	-0.354	21.869	0.000
		3	0.234	0.120	26.032	0.000
		4	-0.448	-0.345	41.571	0.000
		5	0.331	-0.109	50.166	0.000
		6	-0.133	-0.143	51.578	0.000
		7	-0.051	-0.081	51.789	0.000
		8	0.081	-0.267	52.334	0.000
		9	-0.073	-0.138	52.776	0.000
		10	0.156	0.058	54.830	0.000

Source: Calculated using Eviews 7

6.6.2 Runs Test

Tables 6.10 and 6.11 show the run test statistic for the daily and monthly NSM returns respectively. The run test statistics are listed in Table 6.10 for the daily NSM stock returns. As it can be read from this table, run test of serial independence provided very significant Z-statistics with extremely low p-values for each of the time periods, which strongly suggests the rejection of the independence null in the stock returns for NSM. These results are consistent with the previous findings of serial correlation tests that the NSM return series are not following random walk model.

The mean values were positive for all the three period of the study which indicates evidence against the null hypothesis of independence in NSM return series. Thus, we can accept the hypothesis that the NSM is not weak form efficient for daily data.

Table 6-10: Run Test for NSM Daily Stock Returns

Series of returns	No of Obs.	Test Value	Cases >= Test Value	Cases < Test Value	Number of Runs	Z	P-Value
Over All	2592	0.059	1195	1397	942	-13.723	0.000
Pre-reforms	1130	0.134	519	611	429	-7.985	0.000
Post-reforms	1462	0.003	669	793	504	-11.739	0.000

Source: Calculated using PASW Statistics 18 (The test value is the mean)

Table 6-11: Run Test for NSM Monthly Stock Returns

Series of returns	No of Obs.	Test Value	Cases >= Test Value	Cases < Test Value	Number of Runs	Z	P-Value
Over All	132	1.183	63	69	52	-2.603	0.009
Pre-reforms	60	2.540	30	30	26	-1.302	0.193
Post-reforms	72	.053	33	39	25	-2.809	0.005

Source: Calculated using PASW Statistics 18 (The test value is the mean)

Table 6.11 shows that the Z statistics of overall period (-2.603), post-reforms (-2.809) are negative and their p- values less than 0.01 , which show that their actual number of runs fall short of the expected number of runs at 1% significance level which indicate that the result supports the finding of serial correlation tests at 1%. The result for pre-reforms period was different with Z statistics equal -1.302 and p-value 0.193, thus this result does not support the finding of serial correlation tests at 5% significance level.

The above results were supported by the positive mean value. The mean value for overall period 1.183, 2.540 for pre-reforms and 0.053 for post-reforms periods disagree with the random walk model which postulates zero mean. The positive mean value indicate evidence against the null hypothesis of independence in NSM return series. Thus, we can accept the hypothesis that the NSM is not weak form efficient.

In summary, to test the EMH in NSM, three of the widely used standard tests were employed to examine the linear dependence in the daily and monthly returns. For Daily data both ACF and Ljung-Box tests provided a strong evidence of serial correlation in all of the periods of study (Overall period, pre-reforms and post reforms). Similarly, a strong evidence of serial dependence was concluded by the run test for each series. The results of ACF and run tests based on daily data suggested that stock returns are negatively correlated. In addition, ACF showed a strong presence of first-order correlation in all periods of study. As a result, we rejected the hypothesis of market efficiency in its weak form. This finding is supported by a similar study done by Emenike (2008), where he found that the NSM is not weak-form efficient across the time periods that he used in his study.

6.6.3 BDS Test

The results of the BDS test for daily data are reported in Tables 6.12, 6.13 and 6.14 where BDS statistics is respectively listed in the second column with the associated p-values in last column. The results of BDS test indicate extremely small p-values for all the three periods of the Nigerian Stock Market and hence the null hypothesis of i.i.d daily stock returns should be strongly rejected even at the 1% significance level for each time period.

Table 6-12 BDS test result for daily return (2000-2010)

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.0616	0.0019	32.1150	0.0000
3	0.1046	0.0030	34.3280	0.0000
4	0.1298	0.0036	35.7963	0.0000
5	0.1414	0.0038	37.4482	0.0000
6	0.1432	0.0036	39.3395	0.0000
7	0.1389	0.0033	41.6812	0.0000
8	0.1318	0.0029	44.7722	0.0000

Source: Calculated using Eviews 7

Table 6-13 BDS test result for daily return (2000-2004)

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.0446	0.0029	15.5247	0.0000
3	0.0775	0.0046	16.9794	0.0000
4	0.0953	0.0054	17.5288	0.0000
5	0.1005	0.0057	17.7224	0.0000
6	0.0980	0.0055	17.9057	0.0000
7	0.0923	0.0050	18.3913	0.0000
8	0.0861	0.0044	19.3818	0.0000

Table 6-14 BDS test result for daily return (2005-2010)

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.0709	0.0025	28.0046	0.0000
3	0.1197	0.0040	29.7523	0.0000
4	0.1499	0.0048	31.2575	0.0000
5	0.1665	0.0050	33.2945	0.0000
6	0.1720	0.0048	35.6488	0.0000
7	0.1698	0.0044	38.3664	0.0000
8	0.1635	0.0039	41.7567	0.0000

Tables 6.15 to 6.17 reported the BDS result for monthly data. For both overall and post reforms periods the results indicate small p-values for the market and hence the null hypothesis of i.i.d monthly returns should be rejected at 1% level of error for the three periods. On the other hand, for pre-reform period, there is evidence to accept i.i.d. monthly returns at 5% significance level most of the dimensions.

Table 6-15 BDS test result for monthly return (2000-2010)

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.0251	0.0069	3.6510	0.0003
3	0.0533	0.0120	4.8647	0.0000
4	0.0651	0.0131	4.9705	0.0000
5	0.0650	0.0137	4.7430	0.0000
6	0.0616	0.0133	4.6409	0.0000
7	0.0607	0.0122	4.9657	0.0000
8	0.0568	0.0108	5.2381	0.0000

Table 6-16 BDS test result for monthly return (2000-2004)

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.0296	0.0088	3.3502	0.0008
3	0.0310	0.0142	2.1857	0.0288
4	0.0387	0.0170	2.2710	0.0231
5	0.0259	0.0179	1.4458	0.1482
6	0.0066	0.0175	0.3776	0.7057
7	0.0005	0.0162	0.0310	0.9753
8	0.0087	0.0145	0.6019	0.5472

Table 6-17 BDS test result for monthly return (2005-2010)

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.0189	0.0107	1.7617	0.0781
3	0.0550	0.0172	3.1908	0.0014
4	0.0724	0.0208	3.4824	0.0005
5	0.0773	0.0220	3.5203	0.0004
6	0.0758	0.0215	3.5294	0.0004
7	0.0755	0.0110	3.7843	0.0002
8	0.0711	0.0179	3.9755	0.0001

6.7 Summary and Discussion

This chapter mainly examines the Efficient Market Hypothesis (EMH) in the Nigerian Stock Market by exploring the conventional linear approach, using the Autocorrelation Function (ACF) test, Ljung-Peirce test, and the runs tests. In addition, this study employs these linearity tests, as well as nonlinearity tests in stock markets returns using BDS test.

Critical discussion of the results in different periods:

RQ1 I*s the Nigerian Stock Market (NSM) efficient (at least in the weak-form sense of the Efficient Market Hypothesis?)*

The chapter explored the weak-form efficiency of the NSM using the random walk model to test for i.i.d residuals in NSM returns. A battery of parametric and nonparametric tests were used in the analysis, including conventional linear approach, using Autocorrelation Function (ACF) test, Ljung-Box Q statistic, runs tests, and nonlinearity test in form of the BDS test. Both linear and nonlinear methods indicated a significant serial dependence in daily and monthly returns. This can clearly be considered a contradiction to the EMH in its weak form, and hence an evidence of market inefficiency in the NSM.

The runs and BDS tests indicate that the null hypotheses of linear and i.i.d. returns are strongly rejected for each series for overall and post-reforms periods, with the exception of monthly returns data for pre-reforms period. This generally supports the presence of nonlinearity in Nigerian stock market returns. The difference between this period and the post-reforms period 2005-2010 which spans the 2007-09 global financial crises suggests that the 2004 bank reforms and the financial crisis induced chaotic fluctuations in the NSM. This chaotic behaviour may be associated with the presence of speculative bubbles, anomalies and excess volatilities in the NSM, which need to be examined using powerful techniques. These techniques include nonparametric tests for anomalies, stochastic volatility (SV) and (generalised) autoregressive heteroscedasticity (ARCH/GARCH) models for volatility, and duration dependent tests for bubbles.

Furthermore, the general departure of NSM returns from the random walk model due to weak-form inefficiency and plausible nonlinearities in the returns suggest the presence of distortions in asset pricing and risk. This implies that one should expect some stocks in the market to be overvalued or undervalued, that is, mispriced. This explains the increasing interest in foreign investors in the market in search of such arbitrage opportunities to improve their investment returns. There is therefore a possibility that hardworking market analysts could outperform the market averages. This will require good mix of fundamental analysis on individual stocks in specific market sectors, to enable the analysts to identify the stocks that are truly mispriced.

From the policy making perspective, the weak-form inefficiency of the NSM in the pre- and post-reforms periods may be due to some market imperfections which should be corrected with continuing reforms and regulations. These include deepening the market by requiring foreign and local firms to list in the market as a condition for operating in the country, improving transparency and best practice in the NSM, among other policies. Also, the fact that the banking reforms appear to have degraded the efficiency of the NSM compared to the pre-reforms period casts doubts on the efficacy of the reforms and suggests that regulatory reforms should be introduced to reduce moral hazard, lack of transparency in financial transactions and reporting, among other market imperfections. It is therefore particularly important to monitor to what extent current policies being introduced by the SEC actually improve NSM efficiency and performance.

The chapter clarifies the nature of deeper characterisation of the NSM and other emerging African markets which will enhance financial services performance and boost economic development in Nigeria and Africa. Immediate future work on the financial economics side of this characterisation should be to extend the research underpinning this chapter to key market characteristics as suggested above and replicate the entire work at sector- and company-specific levels in the markets.

With respect to the objectives of this study, the chapter critically examines the literature base on market efficiency tests and meanings in order to support future work (**Objective 1**). The chapter also examines suitable models for testing market efficiency and their statistical properties in a way that informs future work on market efficiency at sector and company levels (**Objective 2**). The policy implications of the chapter results are also discussed in light of investment decisions, stock market development and financial policy making (**Objective 3**). The ideas in the chapter are also linked to other market characteristics for example volatility in Chapter 9 of the thesis as well as welfare economics and development in Nigeria (see also Chapter 10 of the thesis).

CHAPTER 7: RATIONAL SPECULATIVE BUBBLES

7.1 Introduction

A speculative bubble is a period when stock prices rise to unsustainable levels. Bubbles in a stock market arise when stock prices are not at the levels that are consistent with economic activity. Slawski (2008, p2) states that " A bubble is defined as that portion of the equilibrium price over and above the market fundamental. The market fundamental is the maximum buy-and-hold-forever valuation of the asset. ".

As noted in Chapter 6 an important feature of a financial market is whether it is efficient in transmitting information and allocating resources to different economic activities in an economy. As mentioned in the chapter, the NSM was inefficient. Other features which are related to market efficiency are predictability, bubbles, anomalies, and volatility. The last two are explored in Chapters 8 and 9 of this thesis.

The existence of bubbles in a financial market contributes to market inefficiency in the sense that they create additional price risks and increase the instability of the market and economy, Binswanger (1999, p116). Generally, price bubbles in a financial asset for example bank shares lead to prices that are much higher than the true or fundamental values of the shares. The bubbles collapse when these prices are no longer sustainable and risk-averse investors prefer to trade in other assets in order to avoid the risks of overpaying for the shares.

Apart from bubbles, other market imperfections can lead to such asset miss-pricing which when corrected by the market could create huge losses to investors. An example of such imperfections is lack of transparency in market transactions whereby management of some companies do not report the true position of the companies, so investors are miss-informed. For instance, recently in Nigeria a number of banks lost market values as a result of management malpractices, in addition to negative effects of the 2007-09 global financial crises.

It is, therefore, important to investigate the presence of rational speculative bubbles in the NSM; indeed, the correct detection of rational bubbles will help policy makers in the Nigerian Stock Exchange (NSE) and the Securities and Exchange Commission (SEC) to implement policies aimed at limiting the presence of bubbles and making the market more efficient.

The detection of rational speculative bubbles in the NSM also has implications for investors. From the investors' point of view even though the price bubbles allow them to earn abnormal profits, the existence of price bubbles will make them aware of the size of the bubbles that could help to detect early signals on the possibility of share price crash. Hence, the information on bubbles forces investors to act realistically by selling assets and adjusting stock prices to fair value; this makes the market to be more efficient.

There is limited study of bubbles on the NSM in the literature. Also, there is no comprehensive study of the crucial financial issues of the emerging stock market (for example, efficiency, anomalies and volatility) which may be associated with rational speculative bubbles in the Nigerian stock market. Therefore, there is a need to correctly identify and analyse the existence of rational bubbles in the NSM by applying a suitable approach.

Objectives of the chapter

The objectives for this chapter are as follows:

- To test whether rational speculative bubbles exists in the NSM (RQ 2) by employing duration dependence test (based on Logistic hazard model) on the returns data in Chapter 5.
- To obtain test results for overall, pre-reform and post-reform periods (RQ 5) and discuss the policy and investment strategy implications of the results for stock market development and financial policy in Nigeria (RQ 6).

7.2 The Concept of Bubbles

Stock market speculation is a process by which investors buy or sell stocks in order to realise capital gains; this activity results in movements of stock prices which are not economically or financially justifiable and is such that the prices are different from the fundamental values of the stocks, Islam and Watanapalachaikul (2005, p 92). The abnormal difference between prices and the fundamental values is referred to as price bubble. A bubble can also be associated with other financial quantities for example returns if there is a significant difference between actual returns and fundamental returns measured by the expected returns in future given current information in the market. There are different concepts of bubbles including rational, irrational, intrinsic, informational, and fads.

Rational bubbles exist in a stock market when stock traders are rational in their behaviour but maintain stock prices which are different from the fundamental values of stocks, in the expectation that they will realise enough profit from the stocks in future to compensate for the prices at which they buy the stocks.

Irrational bubbles occur when trading does not follow rational expectations of reward compared to fundamental values for example trading according to 'herd instincts' (because others are doing so), trading for mere personal satisfaction or because of noise instead of valuable information in the market.

We express bubbles (b_t) as the difference between actual prices (p_t) and fundamental values of stocks (f_t) as follows:

$$b_t = p_t - f_t .$$

The bubbles are rational when traders know that the actual prices are higher than fundamental values, but still trade in the hope that they will realise future profits which compensate their risk of buying the stocks at high prices.

Bubbles are irrational when traders buy or sell rising or falling stocks at higher or lower prices than can be rationally expected in the market, due to other reasons mentioned above.

Bubbles arise mainly because of excessive optimism on the part of traders which leads them to consider that rising or falling prices will be sustained so that they benefit from arbitrage opportunities represented by the differences between prices and fundamental values. However, in the long run such prices are not sustainable so that the bubbles inevitably collapse or burst.

7.3 Different Models for Bubbles

Rational Bubble

The first studies of speculative bubble were made by macroeconomists to formalize the possibility of bubbles which grow with time and are termed 'growing bubbles'. Under rational expectations hypothesis, at time *t* the price of an asset is a function of the expected dividends and the expected value of the price at which the asset can be sold in the next period given currently available information. This can be formulated as (Equation 7.1):

$$P_t = [E(D_{t+1}|I_t) + E(P_{t+1}|I_t)]/(1+r) \qquad \text{Equation 7-1}$$

$$= \frac{1}{(1+r)} E_t(P_{t+1} + D_{t+1})$$

where P_t is the real stock price at t, D_{t+1} is the dividend paid to the owner of the stock between *t* and *t+1*, r is the constant rate of return and thus $0 < (1+r)^{-1} < 1$ is a constant discount factor; and E_t denotes the mathematical conditional expectation operator for given available information at time *t*.

The second type of bubble is a stochastic process for which the next period bubbles at time *t + 1* grow randomly in line with rationally expected returns plus a random error. Denote rational bubbles at time *t* by b_t and let u_{t+1} be an error term which can either be additive or multiplicative. Additive random errors are defined as:

$$b_{t+1} = \lambda_{t+1} b_t + u_{t+1} \qquad \text{Equation 7-2}$$

where λ_{t+1} is a random variable such that the expected value of λ_{t+1}, $E\lambda_{t+1}$ is *1+r*. in addition, bubbles with a multiplicative random error are defined as:

$$b_{t+1} = \lambda_{t+1}(b_t u_{t+1}). \qquad \text{Equation 7-3}$$

Intrinsic Bubble

Froot and Obstfeld (1991) promoted a model in which the price growth underlying a bubble is demonstrated by the assets fundamental value. This formula can be set as:

$$P_t(D_t) = P_t^{pv} + B(D_t) = P_t^{pv} + cD_t^{\lambda} \qquad \text{Equation 7-4}$$

Where P_t^{pv} is the current value of the asset at time *t*, cD_t^{λ} is computed by the dividends discounted continuously compounding. $B(D_t)$ is the bubble element that relies on the dividends and it is supposed that $B(D_t) = cD_t^{\lambda}$, where λ is the positive root of the quadratic equation

$$\lambda^2 \frac{\sigma^2}{2} + \lambda\mu - r = 0 \qquad \text{Equation 7-5}$$

In the above equation, an intrinsic stock-price bubble is generated by a geometric martingale

$$d_{t+1} = \mu + d_t + \xi_{t+1}$$

where *r* is the expected growth rate of the bubbles, μ is the trend growth in dividends, d_t is the log of dividends at time *t*, and given the information at time *t*, ξ_{t+1} is a random variable with conditional mean zero and variance σ^2.

The model of intrinsic bubble relies on dividend values that are used as a proxy for the fundamentals. Furthermore, the bubble in this case is due to an overreaction to the "news" about the dividends. Being dependent on news about changes in dividends which traders rationally incorporate into their buying decisions, the above intrinsic bubble represents a particular kind of rational bubble.

Informational Bubbles

Every type of fundamental asset value is conditioned on relevant market information being available to all the traders. If the prices do not reflect all the available information then they diverge from the intrinsic value which allows an informational bubble to exist.

Grossman and Stiglitz (1980) prove that if the information is pricey, informationally efficient markets are infeasible. That is due to the fact that if the prices reflected entirely all the available information the traders would have no motive to pay to gather information, because they would attain no advantage. If no one gathers information the market cannot sum them and thus cannot be informationally efficient. Hence, prices that completely reflect the fundamental value are paradoxical, this contradiction is often resolved by assuming that the prices deviate from the fundamental value so that informational bubbles are found in the market.

Some models show that the investors in early stage of trading in a market have a motive to gain information because they can make profit, as a result, the market in the early stage is not able to accommodate all the information and thus informational bubble can exist.

Lee (1998) constructed a model in which market information is spread as private signals throughout the market. In the model investors choose between using their own private signals and the previous decisions of investors, therefore, the present market prices. A failure of information aggregation happens because investors put too much weight on past price history. He named this momentum style as information cascades. These cascades are flimsy because they are promoted on the basis of very modest information and on the performance of other investors.

The presence of informational bubble is due to investors' use of diverse information or dissimilar models in their investment options. Therefore, the element that can lead to an increase in speculative bubble is lack of aggregation of the overall information by the investors.

Fads

The various assets markets prices can shift away from their fundamental values because social forces produce fashions in asset markets such as occur in the cars, foods, houses and entertainment markets. A fad can be defined as a deviation between prices and intrinsic value that slowly reverse its mean to zero, Camerer (1989).
This can be as follow:

$$P_t = \sum_{i=1}^{\infty} \frac{E(D_{t+i})}{(1+r)^i} + F_t \qquad \text{Equation 7-6}$$

With $F_{t+1} = cF_t + e_t$, where F_t is a bubble contributed by the fashion element that gradually relapses to its mean of zero, c is a parameter that represents the speed of convergence or decay of the fashion, and e_t is the independent error term with zero mean. If $c=0$ the fad will vanish straight away while if $c=1+r$ the fad will correspond to a rational bubble. The fad is not rational if c is smaller than one (since the anticipated return on the faddish element of the price will be smaller than r and the investors ought to sell the asset, resulting the fad vanishing). Nevertheless, if c is near to one, the fad might be so slow to decompose that investors cannot simply make profit by betting on it to fade away, Camerer (1989).

Remarks

Note that there are some intuitive connections among equations 7.4-7.6. Equation 7.4 simply states that the current price at time t of an asset is a sum of two components, one representing the fundamental value and the other representing the bubbles, expressed as a function of the dividend. Also, the right hand side of equation 7.4 asserts that the bubbles component is itself a polynomial function of the dividend with exponent λ which is determined from equation 7.5. The link between equations 7.5 and 7.6 is the fact that the infinite series in 7.6 is an expression of the fundamental value in terms of the dividend, while the additional component of that equation F_t is the bubbles component which corresponds with the polynomial function in 7.4, whose exponent as already noted is given by roots of equation 7.5. We note that the polynomial function approximation of bubble effects in a financial market is just one way to capture the presence of bubbles, since any other non-negative function which is monotone increasing in the dividend argument can be used. We do not pursue these details further in this thesis.

Since the existence of bubbles in stock market is not something new as it has been mentioned early, several studies using different techniques and approaches have been developed to identify the existence of rational bubbles in stock price and returns.

7.4 How to test rational speculative bubbles

There are several methods and techniques used to detect price bubbles in the stock market. Financial market researchers group these approaches into four main categories: tests for bubble premiums; tests for excess volatility; tests for the co-integration of prices and fundamental variables (mainly dividends); and the duration dependence test e.g Mokhtar et al. (2006), McQueen and Thorley (1994), Delong et al. (1990) and Brooks and Katsaris (2003).

Tests for bubble premiums

The excess returns of the investors claim over the fundamental return is a concept known as a bubble premium and that is viable when rational speculative bubble exists. If this return rises geometrically over time, then it will have an explosive nature. Furthermore, this return is included into the real excess return of the stock over the risk free rate, Mokhtar et al. (2006).

Several researchers used this model to investigate the presence of bubbles in stock market such as Hardouvelis (1988) when he studied the existence of a bubble premium in New York, London and Tokyo stock market indexes from 1977 to 1987. His findings demonstrate that the model predicted real excess returns from 1977 to 1985 but parameter stability tests suggest that the model was not stable after March 1985.

The same conclusion is drawn by DeLong et al. (1990) by monitoring the closed end funds premium for the same period. Their investigation finds that differences in fund managers' and investors' expectations of future earnings may have caused irregular increases in premium, as investors have been blamed for over-optimistic expectations in the time period leading up to October 1987 Crash.

Nevertheless, the broad literature explains that this test for the existence of a bubble premium encounters severe problems and, consequently, is not capable to verify or sufficiently deny the presence of rational speculative bubbles.

Tests for excess volatility

A dissimilarity technique of examining bubble presence is by testing stock market's variance and tests application for excess volatility. In general, if a speculative bubble exists, the stock price variance will be larger than the variance of fundamental price, Brooks and Katsaris (2003).

Brooks and Katsaris (2003, p328) stated "*Tests for the presence of excess volatility are based on a comparison of the variance of actual prices with the variance of fundamental prices. In most cases, the fundamental prices are constructed using ex post analysis, but several researchers try to model and forecast dividend series in order to construct fundamental prices that are similar to the prices perceived by investors*".

Discussion has been conducted in the literature according to the relationship between speculative bubbles and the volatility of price. For example, Hart and Kreps (1986) explained that speculative bubbles could cause a considerable increment in price volatility when Marsh and Merton (1986) stated that the variance bound methodology is apparently powerful.

To conclude, Flood and Garber (1980) declared that the examination of variance bounds were not reliable. In fact, they debated that the major fundamental price construction models were mis-specified because most of the models eliminated relevant variables, etc. Moreover, the dividends and price series that are used in the tests of variance bounds were non stationary, which in turn might lead to biased variance estimations.

Tests for the co-integration of dividends and prices

The third method is called non-stationary or the co-integration test for dividends and prices. Brooks and Katsaris (2003) demonstrated that if the stock price relies solely on future dividends; and if there are no realistic speculative bubbles and if dividends are also stationary in the mean, therefore, as a result prices will be stationary. Nevertheless, if dividends and prices are non-stationary, if they are co-integrated thus the hypothesis of no-bubble cannot be denied. However, the lack of co-integration is an insufficient condition to verify the presence of bubbles since the model may rule out considerable variables that influence stock prices.

Numerous researchers used and developed this method such as, Campbell and Shiller (1987); Craine (1993); Fama and French (1998) and Summers (1986). They brought out a similar conclusion after examining the dissimilarity of prices and discounted dividends for stationarity. They confirmed that prices pursued a stationary procedure in the short-term, but this procedure might differ in the long-term horizons. The conventional current value model may not hold as a reason of the existence of bubbles that cannot be perceived.

Duration Dependence Test

Duration dependence technique suggested by McQueen and Thorley (1994) is based on the statistical theory of duration dependence and was originally examined in the US stock market. It proposes that if security prices enclose bubbles, then runs of positive irregular returns will reveal negative duration dependence (declining risk rates), which is a distinctive feature of rational speculative bubbles.

Harman and Zuehlke (2004) explain that duration dependence is a feature of the risk function for duration times. If $f(t)$ indicates the density function for duration times, and $F(t)$ is the corresponding distribution function, then the risk function $h(t)$ is given as the conditional density for duration of length t, provided that the duration is not less than t, that is

$$h(t) = f(t)/(1 - F(t)), \text{ where } 1 - F(t) = \Pr(T \geq t). \qquad \text{Equation 7-7}$$

The risk function shows positive (negative) duration dependence if $h(t)$ increases (decreases) in t. Thus, the model of McQueen and Thorley (1994) forecasts the risk function for a run of positive irregular returns that is a declining function of the run length. See further details below. Numerous researchers are in favour of the method of duration dependence relying in deferent series data adopted from different countries.

Jirasakuldech et al. (2006) tested the existence of rational speculative bubbles Equity Real Estate Investment Trusts (REIT) using the 1973-2003 monthly price index for REITS and the Russell 2000 index in the US. There is no increasing or decreasing pattern in the hazard rate either in REIT index or Russell 2000 index. Neither of the index shows evidence of duration dependence, suggesting that REIT markets and small stocks are not affected by rational bubbles. Harman and Zuehlke (2004) tested the evidence of rational speculative bubbles based on monthly abnormal returns of all NYSE stocks from 1927 to 1997 and weekly abnormal returns of NYSE-AMEX indices from 1963 to 1997. Monthly data using both the discrete Weibull and Log-logistic models show evidences of speculative bubbles for value-weighted portfolios.

Jaradat (2009) inspected whether equity costs in Jordanian stock market are distinguished by rational speculative bubbles in duration period from 1992 to 2007. The appreciations of duration dependence examinations are tested on positive and negative runs of the actual returns with Weibull risk function. Aman Stock Exchange returns (ASE) index show negative duration dependence in runs of positive returns, however, not in runs of negative returns, compatible with the existence of rational bubbles.

Employing both weekly and monthly irregular market returns of Shanghai and Shenzhen A- and B-markets Lehkonen (2010) used duration dependence examination for rational bubbles in Chinese stock markets as well as China-related share indices in Hong Kong. He came up with the results that bubbles existed in weekly data for both the Mainland Chinese stock exchanges' share classes. The results also show that there was no evidence of rational bubbles in Hong Kong stock market in either weekly or monthly returns.

In conclusion, the duration dependence test, either using Log Logistic or Weibull's Hazard Model, or with both hazard models, has been more widely accepted in detecting rational speculative bubbles in stock prices today.

However, decision to accept or reject the existence of rational speculative bubbles in stock market seems to be very difficult to the extent that some scholars ask whether bubbles can be detected or not? Thus, Gurkaynak (2008, p1) tried to answer the question "can asset price bubbles be detected?". His study of econometric tests of asset price bubbles shows that, " *despite recent advances, econometric detection of asset price bubbles cannot be achieved with a satisfactory degree of certainty. For each paper that finds evidence of bubbles, there is another one that fits the data equally well without allowing for a bubble*".

7.5 Data and Adopted Models

The objective of this chapter is to investigate whether rational speculative bubbles are present in the NSM. To achieve this goal two modelling objectives have been set. Firstly, preliminary test of whether rational speculative bubbles exist in NSM is performed using evidence from skewness, leptokurtosis and autocorrelation of the return series described in Chapter 5. According to McQueen and Thorley (1994)[23], negative skewness, leptokurtoses and positive autocorrelations in return series indicate the presence of bubbles in the market. However, some researchers such as Chan et al., (1998) have a concern about this test because such statistical results may be driven by factors unrelated to bubbles.

Secondly, we apply the duration dependence test (using log logistic model approach) to detect rational speculative bubbles in the NSM. As described in Chapter 5, the test period will be from 2000 to 2010, and will be divided into pre-reforms (2000-2004) and post-reforms periods (2005-2010).

7.5.1 Data collection and limitation

According to the previous studies several kinds of data had been used to investigate the existence of rational bubbles in stock markets. For instance, Parvar and Waters (2010) used price index, market value, and dividend series from Middle and North African (MENA) countries to study Equity price bubbles in these markets.

Using monthly price indexes and reliable dividend yields data, Yu and Hassan (2009) examined the possibility of rational speculative bubbles in Organisation of Islamic

[23] See also Martin et al. (2004).

Countries (OIC) stock markets. Gurkaynak (2008) used indexes and dividend yields data to econometric tests of asset price bubbles. Mokhtar et al (2006) studied the existence of rational speculative bubbles in Malaysian Stock Market using different set of data including composite index, property index, finance index, construction index plantation index, consumer price index, trading and services index and industrial product index.

In most of developing countries getting the data is a big challenge for researchers. To launch an empirical study on bubble testing for NSM both monthly and weekly data for NSM all share indexes were used in this study. The period of study is from 2000 to 2010. Because of the shortness of the time series for monthly data we used the whole period without dividing it into sub-periods. Weekly returns are divided into pre-reforms (2000-2004) and post-reforms (2005-2010) periods. Several reasons are given by some researchers in finance for using monthly and weekly data. Firstly, monthly data are less susceptible to noise, while weekly returns are not. As a reason of the shorter data which can be obtained by adopting monthly data, there will be a lack of power of the test as is noted by Lehkonen (2010) when he found that the duration dependence is sensitive to the use of monthly versus weekly runs of abnormal returns. Secondly, if there is no clear indication about the length of a bubble, it is recommended to use both of the returns in order to make our results more robust.

7.6 Evidence for the Modelling Approaches for Detecting Rational Speculative Bubbles

Preliminary test for rational speculative bubble uses three key characteristics of distributions of asset prices or returns which are skewness, leptokurtosis and autocorrelation. McQueen and Thorley (1994) demonstrated that a negatively skewed value-weighted portfolio together with considerable excess kurtosis and first-order autocorrelation coefficients are compatible with the model of bubbles during post-World War II subsample period.

Chan et al. (1998) also extracted that the features of Asian stock return distributions are consistent with rational speculative bubbles that based on the summary statistics of returns. The model of rational speculative bubble involves negative skewness, positive autocorrelation and the return series are leptokurtic. Jaradat (2009) specified that the ASE (Amman Stock Exchange) returns in Jordanian stock market display considerable skewness and leptokurtosis, which indicate the existence of bubbles. In addition, the other studies of rational bubbles also involve positive autocorrelation in returns[24].

To investigate the existence of rational bubbles in NSM, the Duration Dependence test is chosen using the discrete log logistic model developed by McQueen and Thorley (1994) as the most feasible tool to detect rational bubble. Supported by many researchers, duration dependence tests proposed by McQueen and Thorley (1994) have been widely accepted for studying speculative rational bubbles in financial market. For example, Cameron and Hall (2003) examined the impact of short -term fund performance and annual fund performance on both the fund's hazard function and the fund's survivor function. The y show an asymmetric response to mutual fund performance, with positive shocks having a larger impact on hazard rate than negative shocks. Watanapalachaikul and Islam (2007, p6) also employed Dependence test and Webull Hazard model to test for existence of rational speculative bubbles. They stated " *the model of speculative bubbles as given by McQueen and Thorley (1994) allows stock prices to deviate from their fundamental values without assuming irrationality on the part of market participants. The Weibull Hazard model is widely accepted, because of its robustness in testing for rational speculative bubbles. It is also used as a benchmark for studies of duration dependence tests*".

This study applies duration dependence test using the log-logistic models for the detection of rational speculative bubbles in NSM. The sample hazard rate for each length *i* can be estimated from maximizing the log likelihood function of the hazard function. According to Blanchard and Watson (1982), Evans (1986) and McQueen and Thorley (1994), to apply the duration dependence test, the returns need to be transformed into series of run lengths on positive and negative observed abnormal returns.

7.6.1 The logic of the duration dependence test

The theoretical model of rational speculative bubbles discussed in McQueen and Thorley (1994) suggests that bubbles are associated with explosive changes in prices or returns. Hence, the bubble grows stronger the longer positive abnormal returns last. This means that the probability that a run of abnormal positive returns ends after a run length

[24] For more result see Jirasakuldech et al. (2007), Hassan and Yu (2007) and Haque, et al. (2008).

i decreases with i when there is a rational speculative bubble in the data. This is simply because market participants continue to invest in the underlying asset in the hope of making compensating profits from the positive returns. This characteristic for which the conditional probability of a run of positive abnormal returns ending, given its duration or length i, is a decreasing function of i is called negative duration dependence.

As in McQueen and Thorley (1994), a run is defined as a sequence of abnormal returns of the same sign. To explain how to transform the return we provide the following example.

A return series of two positive abnormal returns, followed by one negative abnormal returns, five positive and, finally, four negative abnormal returns is transformed into two data sets: a set for the runs of positive abnormal returns with values of 2 and 5; a set for the runs of negative abnormal returns with values of 1 and 4.

As mentioned above, consider a returns or price data measured continuously over time T with values t, so that appropriate durations of runs are continuous. Let f(t) denote the density function of duration times, F(t) the corresponding distribution function, then the hazard rate h(t) is the conditional density function of T for duration of length t, given that duration is not less than t; that is

$$h(t) = \Pr[T = t \mid T \geq t] = \frac{f(t)}{\Pr[T \geq t]} = \frac{f(t)}{1 - F(t)} \qquad \text{Equation 7-8}$$

The hazard rate h(t) shows positive or negative dependence if it increases or decreases in t. As explained above, the model of McQueen and Thorley (1994) predicts that for a run of positive abnormal returns $h(t)$ exhibits negative dependence.

The most commonly used hazard model is associated with the Weibull distribution which is used to study the time to failure of products in reliability engineering. According to Harman and Zuehlke (2004, p2), the distribution function of the Weibull hazard model (the Weibull distribution) is given by

$$F(t) = 1 - \exp(-\alpha t^{\beta+1}) \qquad \text{Equation 7-9}$$

where $\alpha > 0$, $\beta > -1$, and $t > 0$. The parameter β is the duration elasticity of the hazard function. The corresponding density function is

$$f(t) = \alpha(\beta + 1)t^{\beta}[\exp(-\alpha t^{\beta+1})] \qquad \text{Equation 7-10}$$

Therefore, the hazard function *h(t)* is given by

$$h(t) = \frac{f(t)}{1-F(t)} = \frac{\alpha(\beta+1)t^{\beta}\exp(-\alpha t^{\beta+1})}{\exp(-\alpha t^{\beta+1})} \qquad \text{Equation 7-11}$$

$$\therefore h(t) = \alpha(\beta+1)t^{\beta}; \quad \alpha > 0, \beta > -1, t > 0$$

Since *h(t)* in equation 7.11 is monotone in t, it increases with t if β is positive and decreases with t if β is negative. Hence, testing for bubbles using this hazard function is testing for whether β is significantly negative in the data series (in this research returns data series).

Let J_i be a binary variable that indicates whether an observed duration, t_i, is complete or partial, then the log-likelihood function for a sequence of *N* runs is:

$$\ln L(\alpha,\beta) = \sum_{i=1}^{N}\{J_i \ln[f(t_i)] + (1-J_i)\ln[1-F(t_i)]\} \qquad \text{Equation 7-12}$$

Discrete Log Logistic Model

Even though securities are traded continuously, returns and prices are practically measured in discrete times for example days, weeks and months as is the case with our research data on NSM indexes and returns. Hence, we use a discrete version of the hazard duration model described below.

Let *g(t)* denote the discrete density function for duration, and *G(t)* is the corresponding distribution function. Then the log-likelihood function for a sequence of *N* runs is defined as, Harman and Zuehlke (2004):

$$\ln L(\propto, \beta) = \sum_{i=1}^{N}\{J_i \ln[g(t_i)] + (1-J_i)\ln[1-G(t_i)]\} \qquad \text{Equation 7-13}$$

where α is the shape parameter of the lognormal distribution, β is the duration elasticity of the hazard function, J_i is as explained in equation 7.12 above. The density and distribution functions in equation 7.13 are related as:

$$G(t_i) = \sum_{k=1}^{t_i} g(k) \qquad \text{Equation 7-14}$$

Recall that the hazard function is defined as the conditional probability that T = t given that T is not less than t. In the discrete case, this is given by

$$h(t) = \Pr[T = t \mid T \geq t] = \frac{g(t)}{\Pr[T \geq t, t+1, \ldots]} = \frac{g(t)}{1 - \Pr[T \leq t-1]} \qquad \text{Equation 7-15}$$

$$\therefore h(t) = \frac{g(t)}{1 - G(t-1)}$$

This implies that *h(1)=g(1)/[1-G(0)]=g(1),* hence *G(0)=0* Therefore, as explained in Harman and Zuehlke (2004), this fact combined with successive application of conditional probability law gives the following recursive formula for the discrete density function *g(k)* in terms of the hazard rate *h(k)*:

$$g(k) = h(k) \prod_{m=0}^{k-1} [1 - h(m)] \qquad \text{Equation 7-16}$$

for positive integer durations *k*, where *h(0)* = 0. For this research we will use the following explanation of the hazard function.

Generally, from equation 7.16 above we write the link between the hazard function and density functions as:

$$h_i = \frac{g_i}{(1-G_i)} \; and \; g_i = h_i \prod_{i=1}^{\infty} (1 - h_i) \qquad \text{Equation 7-17}$$

Using the above formula (7.17) in 7.13 the hazard function version of the log likelihood is:

$$L(\alpha, \beta) = \sum_{i=1}^{\infty} (N_i lnh_i + M_i l\,n(1 - h_i)) \qquad \text{Equation 7-18}$$

where N_i the number of complete runs of length *i*; and M_i is the numbers or runs of length greater than *i*. To carry out duration dependence tests, the log-logistic functional formula is selected for the hazard function, which is also similar to McQueen and Thorley (1994).

$$h_i = \frac{1}{1 + e^{-(\alpha + \beta lni)}} \qquad \text{Equation 7-19}$$

The function of log-logistic changes the unbounded range of $\alpha + \beta lni$ into the (0, 1) space of h_i, which is the conditional probability of ending a run. The null hypothesis of no bubbles proposes that a run ending probability is independent from previous returns or that the positive and negative abnormal returns are accidental. In model terms, the null hypothesis of no duration dependence is that β will be equivalent to zero, $\beta = 0$ which implies a constant hazard rate. The bubble alternative proposes that the probability of a positive run ending ought to reduce with the run length or that the slope parameter value β is negative, which means lessening hazard rates. Hence, the tests can be carried out by substituting the formula (7.19) in the equation (7.18) and by maximizing the log likelihood function regarding to α and β.

Remarks: estimating the sample hazard rates

The Hazard rate for i length can be calculated from equation 7.18 as follows. To maximise the likelihood function we differentiate L with respect to h_i and set to zero to obtain:

$$\frac{\partial L}{\partial h_i} = 0 \Leftrightarrow \sum_i [\frac{N_i}{h_i} - \frac{M_i}{1-h_i}] = 0$$

$$\therefore \frac{N_i}{h_i} - \frac{M_i}{1-h_i} = 0 \Leftrightarrow N_i = (N_i + M_i) h_i$$

$$\hat{h}_i = \frac{N_i}{N_i + M_i} \qquad \text{Equation 7-20}$$

7.7 Empirical Results

7.7.1 Sample statistics for returns

Table 7-1 Summary statistics for Weekly return

Series	Mean	Standard Deviation	Skewness	Kurtosis
Over all (2000-2010)	0.2720	3.2411	-0.4581	5.6239
Pre-reforms (2000-2004)	0.5788	2.7667	-0.1986	5.6320
post-reforms (2005-2010)	0.0200	3.5687	-0.4658	5.1621

Table 7.1 presents the summary statistics of weekly returns for NSM. From the table skewness and kurtosis provide similar results for the three series with negative skew and large kurtosis. The strong evidence of negative skewness and large kurtosis coefficients imply the existence of bubbles.

Table 7-2 Summary Statistics for Series Dependence Weekly Returns (2000-2010)

Lag	Autocorrelation	Box-Ljung Statistic		
		Value	df	Sig.[b]
1	.073	3.076	1	.079
2	.058	5.027	2	.081
3	.070	7.841	3	.049
4	.049	9.219	4	.056
5	.102	15.200	5	.010

Table 7-3 Summary Statistics for Series Dependence Weekly Returns (2000-2004)

Lag	Autocorrelation	Box-Ljung Statistic		
		Value	df	Sig.[b]
1	-.010	.026	1	.873
2	.078	1.599	2	.450
3	.013	1.641	3	.650
4	.043	2.138	4	.710
5	-.010	2.164	5	.826

Table 7-4 Summary Statistics for Series Dependence Weekly Returns (2005-2010)

Lag	Autocorrelation	Box-Ljung Statistic		
		Value	df	Sig.[b]
1	.105	3.453	1	.063
2	.037	3.894	2	.143
3	.090	6.456	3	.091
4	.044	7.071	4	.132
5	.147	13.964	5	.016

Tables 7.2, 7.3 and 7.4 show that generally the first-order autocorrelation coefficients are positive but statistically insignificant. Hence, the weekly returns are weakly serially correlated. Therefore, the evidence of autocorrelation is also consistent with the non-existence of rational bubbles in weekly NSM returns.

Table 7-5 Summary statistics for Monthly return

Series	Mean	Standard Deviation	Skewness	Kurtosis
Over all (2000-2010)	1.1833	7.6646	-0.6374	8.6538
Pre-reforms (2000-2004)	2.5396	5.5394	-0.1428	3.0649
post-reforms (2005-2010)	0.0529	8.9465	-0.4788	7.9139

For the monthly data in Table 7.5, as a same result obtained for weekly data all the monthly series are negatively skewed and have large kurtosis, which are consistent with the rational bubble model.

Table 7-6 Summary Statistics for Series Dependence Monthly Returns (2000-2010)

Lag	Autocorrelation	Box-Ljung Statistic		
		Value	df	Sig.[b]
1	.165	3.660	1	.056
2	.165	7.382	2	.025
3	.150	10.463	3	.015
4	-.104	11.953	4	.018
5	.191	17.046	5	.004

The monthly series returns provide positive first-order autocorrelation as it can be seen from Table 7.6 the Q test shows that the autocorrelations at various lags are significant at the 5% level of error; lag 5 autocorrelation is significant at the 1% level of error (*p*-value is 0.004).

Overall, the monthly and weekly return series exhibit negative skewness and high kurtosis coefficients (except monthly pre-reforms where the kurtosis equal 3.0649) which indicate the possible presence of bubbles. The proof implies that stock price departures from fundamental values and changes occasionally by large amounts. The high kurtosis coefficients especially for monthly return also imply that returns are not normally distributed.

From the results above, the evidence of skewness, kurtosis and autocorrelation all suggest that bubbles potentially exist in the NSM, but this is not significant. That is, practically from the summary statistics of the returns data, the NSM does not exhibit undue presence of rational speculative bubbles, so that the differences between actual and fundamental returns may be due to other imperfections in the Nigerian economy and stock market.

However, as mentioned earlier such descriptive statistics as listed above may be influenced by factors unrelated to bubbles. Thus, more specific tests including the duration dependence test is performed to confirm the existence of bubbles in NSM returns at overall market levels. We present the test results in the following section.

7.7.2 Duration dependence test

We now test for the existence of rational speculative bubbles using the Duration Dependence test based on Log- logistic model tests. The closing all share index of the NSM from January 2000 to December 2010 is used in this study to calculate the NSM returns. Both weekly and Monthly data will be used. Four time periods will be investigated, which can be described as:

1. Over all period from January 2000 to December 2010 for Monthly data series.
2. Over all period from January 2000 to December 2010 for Weekly data series.
3. Pre-reforms period from January 2000 to December 2004 for Weekly data series only.
4. Post-reforms period from January 2005 to December 2010 for Weekly data only.

To perform the duration dependence test, first the positive and negative abnormal returns need to be calculated. The idea is to build up a model that can describe and predict the rate of the NSM Index return, (Mokhtar; 2006, Jaradat; 2009, Zhao; 2006, Jirasakuldech, et al., 2007 and Dou; 2010).

The following model is used by McQueen and Thorley to calculate the abnormal return:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 R_{t-2} + \alpha_3 R_{t-3} + \alpha_4 TERM_{t-1} + \alpha_5\, D/P_{t-1} + \varepsilon_t$$

Equation 7-21

where $\mathrm{R_t}$ is the return (as it been mentioned earlier $\mathrm{R_t} = \ln\left(\frac{\mathrm{I_t}}{\mathrm{I_{t-1}}}\right) \times 100$), TERM is the term spread, which is the difference in yield-to-maturity between the Ibbotson Associates AAA Corporate Bond Portfolio and the one-month Treasury bill in the US; D/P is the value-weighted NYSE portfolio's dividend yield calculated by dividing the sum of the previous 12 monthly dividends by the current price. The abnormal returns are defined as the residuals from the above regression, which is the "ε_t" value. McQueen and Thorley (1994) included TERM and *D/P* in the model because Fama and French (1989) found that these two items were useful in predicting time-varying risk premium, Zhao (2006).

The biggest challenge facing researchers in any field and especially in Africa is data availability and collection. In NSM case it is very difficult to get the time series data for both *TERM* and *D/P*. However, in this thesis we will follow (Zhao; 2006 and Dou; 2010) where they used the following adjusted equation to calculate the abnormal returns:

$$\mathrm{R_t} = \alpha_0 + \alpha_1 \mathrm{R_{t-1}} + \alpha_2 \mathrm{R_{t-2}} + \alpha_3 \mathrm{R_{t-3}} + \varepsilon_t \qquad \text{Equation 7-22}$$

Thus, the positive and negative abnormal returns here are defined relative to the sign of the error from weekly and monthly adjusted models. Because the monthly data is too short for monthly pre and post- reforms, monthly pre and post- crises and weekly pre and post crises only the periods pointed above, will used perform the duration dependence test in this thesis.

The calculation of $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ and ε_t (abnormal returns) for each series of data are shown in Appendix 7.1-7.4. The Monthly positive and negative abnormal returns for the period 2000-2010 show also in same Appendix.

Tables 7.7- 7.10 reports the results of duration dependence test based on the Log-logistic model for monthly and weekly abnormal returns series.

Table 7-7 Run Counts, Hazard Rates and Duration Dependence Test for NSM based on Monthly Data 2000-2010

	Positive		Negative	
Run Length	Actual Run Counts Total = 26	Hazard Rates	Actual Run Counts Total =27	Hazard Rates
1	10	0.3846	9	0.3333
2	5	0.3125	6	0.3333
3	5	0.4545	8	0.6667
4	5	0.8333	3	0.7500
5	0	0.0000	0	0.0000
6	1	1.0000	0	0.0000
7			0	0.0000
8			0	0.0000
9			0	0.0000
10			0	0.0000
11			1	1.0000
Log-Logistic Test				
α	-0.6672		-0.5511	
β	0.6329		0.1967	
P-Value	0.3387		0.7418	

Note: The calculation of α and β have carried out by Eviews 7 Software using the command shown in appendix 7.5

Let N_i = number of runs of length *i*, and M_i be the number or runs of length greater than *i*, then the sample hazard rate can be obtained from equation 7.19 as $h_i = N_i/(N_i + M_i)$.

For example, for i=1 there are 10 (N_i) positive abnormal returns, and there are still another remaining 16 runs of positive abnormal returns which will be M_i. The sample hazard rate for the first positive abnormal returns is $10/(10+16) = 0.3846$. Hence the possibility of the positive abnormal return to burst at the end of period one is 0.3846.

For overall monthly period, table 7.7 shows that the longest runs length for monthly abnormal returns is 6 in 2007. A pattern of decreasing hazard rate in positive runs is noted in the first two lengths, which are 0.3846 and 0.3125 respectively. This that there is a 38.46% probability that positive returns lasting for one month and 31.25% for two months will slip back to a negative return in the next period. This pattern drop might indicate the presence of rational speculative bubbles in stock prices associated.

The null hypothesis of no-bubble implies that the hazard rate is constant, which mean $\beta = 0$.The duration dependence test examines whether the hazard rate are downward sloped with the run length i. For monthly data, β is 0.6329 (non-negative) and with the p-value of 0.3387 which leads to acceptance of the null hypotheses of no duration dependence.

The Interpretation of the duration dependence tests on the negative runs is not different from the positive runs since the evidence of rational speculative bubbles cannot be found in the negative returns ($\beta = 01967\ and\ p - value\ =\ 0.7418$).

Table 7-8 Run Counts, Hazard Rates and Duration Dependence Test for NSM based on Weekly Data 2000-2010

Run Length	Positive Actual Run Counts Total =134	Hazard Rates	Negative Actual Run Counts Total =134	Hazard Rates
1	63	0.4701	64	0.4776
2	29	0.4085	28	0.4000
3	23	0.5476	23	0.5476
4	9	0.4737	13	0.6842
5	3	0.3000	4	0.6667
6	4	0.5714	0	0.0000
7	2	0.6667	0	0.0000
8	1	1.0000	1	0.5000
9			1	1.0000
Log-Logistic Test				
α	-0.1761		-0.1605	
β	0.0788		0.1701	
P-Value	0.8396		0.5694	

Table 7-9 Run Counts, Hazard Rates and Duration Dependence Test for NSM based on Weekly Data 2000-2004 (Pre-reforms)

Run Length	Positive Actual Run Counts Total =59	Hazard Rates	Negative Actual Run Counts Total =59	Hazard Rates
1	27	0.4576	25	0.4237
2	18	0.5625	11	0.3235
3	7	0.5000	10	0.4348
4	4	0.5714	7	0.5385
5	1	0.3333	5	0.8333
6	2	1.0000	1	1.0000
Log-Logistic Test				
α	-0.1446		-0.4993	
β	0.3407		0.3995	
P-Value	0.7490		0.3025	

Table 7-10 Run Counts, Hazard Rates and Duration Dependence Test for NSM based on Weekly Data 2005-2010 (Post-reforms)

Run Length	Positive Actual Run Counts Total = 74	Hazard Rates	Negative Actual Run Counts Total =74	Hazard Rates
1	37	0.5000	37	0.5000
2	10	0.2703	16	0.4324
3	15	0.6818	13	0.6190
4	5	0.4167	6	0.7500
5	2	0.2857	1	0.5000
6	3	0.6000	0	0.0000
7	2	1.0000	0	0.0000
8			0	0.0000
9			1	1.0000
Log-Logistic Test				
α	-0.1750		-0.0367	
β	-0.0354		0.1319	
P-Value	0.9098		0.8233	

For overall weekly abnormal there are 567 observations which are categorized into 134 runs, the longest runs length is 9 which emerge during 2008 (table 7.8). Intuitionally, bubbles may possibly exist in this period. For the pre-reforms period (table 7.9) datasets which only include 254 observations, and longest runs length can even reach 6. For the period during 2005 to 2010 (table 7.10), a run with the length of 9 can also be observed in the weekly abnormal return series.

A pattern of decreasing hazard rate in positive runs is noted in the first two lengths for both overall and post-reforms periods, which are 0.4701 and 0.4085 respectively for overall and 0.5000 and 0.2703 respectively for post-reforms periods. This indicate that there is a 47.01% probability that positive returns lasting for one week and 40.85% for two weeks will slip back to a negative return in the next period for overall period and 50.00% probability that positive returns lasting for one week and 27.03% or two weeks will slip back to a negative return in the next period for 2005-2010 period.

As mentioned earlier the null hypothesis of no-bubble implies that the hazard rate is constant, which mean $\beta = 0$.The duration dependence test examine whether the hazard rate are downward sloped with the run length i. That is, the result reflected by β in tables 7.8-7.10. For overall and pre-reforms weekly dataset, β=0.0788 with the p-value of 0.8396 and β=0.3407 with p-value 0.7490 respectively we accept the null hypothesis of no duration dependence. This means that abnormal returns do not exhibit duration dependence.

For post-reforms weekly datasets with negative β (-0.0354) which imply the existence of bubbles in NSM, the p-value of β (0.9098) is insignificant to accept the null hypothesis of β=0. Same decision can be made for the negative abnormal runs where β=0.1319 with p-value = 0.8233.

7.8 Summary and Discussions

This chapter explores the existence of bubbles in NSM returns for the 2000-2010 study period, particularly pre- and post-reform sub-periods. From what has been discussed above it can be concluded that the NSM abnormal returns data do not exhibit duration dependence. In other words, the findings of the duration dependence test further show that rational speculative bubbles are not present in the NSM. This result is consistent with Yu and Hassan (2009) who did not find an evidence of bubbles in Middle East and North African stock markets. It is also consistent with the results obtained by Okpara (2010) for the NSM.

However, recently there were bank failures in key parts of a number of Nigerian banks for example Intercontinental Bank plc, Oceanic Bank plc, and Bank PHB plc. This can be as a result of bubbles in the banking sector and because we are using the overall market NSM indices/returns for this study the existence of bubbles may be masked by offsetting bubble effects in different sectors, so that bubbles do not manifest at the overall market level. Hence, further analyses are needed for some sectors such as banking, telecommunications, oil and gas, agriculture, manufacturing, banking and financial sectors, in order to characterise NSM behaviour at these finer levels of study.

As earlier mentioned in Section 1, *'the existence of bubbles in a financial market contributes to market inefficiency in the sense that they create additional price risks and increase the instability of the market and economy',* Binswanger (1999, p116) and Okpara (2010, p239). The NSM has been shown in Chapter 6 to be inefficient, a fact that is also supported by Okpara (2010). It is noted in Chapter 2 of this thesis and reinforced by Okpara (2010) that distortions in the NSM range from barring foreign investors from entering the market in 1999, imposing price caps on share price movement to interest rate regulation and political instability, all of which contribute to all round low performance of the market. The repercussion effect is thinness of trading, low market capitalization, low turnover, negative performance ratios, low betas, significant abnormal returns and illiquidity of the market.

This study has shown that the above imperfections in the NSM are not due to the presence of rational speculative bubbles. Policy makers should, therefore, use appropriate monetary, fiscal and regulatory tools to correct the imperfections and enhance the performance of the NSM.

However, there are signs of abnormal movements in returns in the summary statistics which suggest that investors and policy makers in Nigeria should monitor the possibility of market bubbles.

We note that there are different methods of testing for the existence of bubbles which are mentioned but not applied in this chapter because of limitations of data. Some of these methods could be used in future work on specific sectors and companies with data that meet their various assumptions. For example, tests for excess volatility and cointegration of dividends and prices could be done for the banking sector in addition to duration dependence tests in order to triangulate the analysis of bubbles in that sub-sector.

With respect to the link between the results in this chapter and the objectives and research questions we set out to explore in the thesis, we state as follows.

The chapter critically reviews the literature base on applied statistical models typically used in the study of bubbles, in order to enable future researchers to benefit from using such models in related work (**Objective 1**). As mentioned above, this literature will also guide future work by applying suitable models for bubbles at sector- and company-specific levels (**Objective 2**).

In terms of the policy implications of the results (**Objective 3**), we note that knowledge of the existence of bubbles will help investors to determine how to realise high returns in the NSM and plan their timing of investments and disinvestments from particular stocks which manifest irrational and speculative bubbles, especially given the fact that the market is weak-form inefficient. For investors to actually achieve this objective they should conduct proper fundamental analysis and valuations of market assets and portfolios.

From the perspective of policy makers, knowledge of bubbles and other market imperfections discussed in Chapters 2-9 of the thesis enables them to plan effective interventions in the market aimed at improving stock market performance, stock market development, financial reforms and policies, and overall economic development of Nigeria. For example, if some assets or asset classes are associated with excessive bubbles for example housing market and bank shares, then the CBN, SEC and NSE will attempt to make macroeconomic policies and produce market regulations that will reduce the bubbles.

Remarks

We note that it is not very easy to identify bubbles in light of effects of shifts in market fundamentals over time. Also different market behaviours or characteristics resemble bubbles for example volatilities and market failure/collapse. Examples of such shifts may be in connection with changing policies on interest rates, for instance, financial reforms and crises which generate and transmit market signals. We have, therefore, provided an understanding of the different types and examples of bubbles out there in the literature (see Chapters 3 and 7). We have also related the existence of bubbles to perceived structural and regulatory imperfections in the NSM which potentially distort the price formation process away from fundamental values. See also Chapter 9 of the thesis on volatility of NSM returns.

Moreover, we make the point that the difficulty in identifying bubbles and the fact that bubbles may be associated with particular stocks and sectors requires us to triangulate the analysis of NSM bubbles in future work and for this study in related analyses in Chapters 7, 8 and 9 of the thesis. Particularly, this is the rationale for using augmented GARCH models to analyse the returns component of the volatility processes in Chapter 9.

Also, we noted in this chapter the kind of additional data that could be used in performing bubbles analysis. We do not have all these data available in this study and recommend that future studies on bubbles in the Nigerian financial system should use the additional data to better identify bubbles, especially at sector and company levels. In order to use the additional variables we may have to use proxy variables if good data on the preferred variables are hard to access in Nigeria. Particularly, in using autoregressive time series (generally non-linear models) to incorporate the effects of these variables in the analysis, we may need to determine more structurally the best fit models as a contribution to knowledge for example using the Akaike Information Criterion (AIC) to determine optimal lags for the models, among other performance criteria.

Additionally, the finding of no bubbles in the NSM is counterintuitive because of the above comments that bubbles may still exist at other market levels for example sectors and companies, and can be confirmed by the use of other models and data.

Finally, we note that bubbles may be masked at overall market level due to data aggregation problems and levelling effect of oil price fluctuations. This suggests the need to link the analyses of bubbles in future work to possible effects of oil prices in light of plausible global correlations in financial markets through oil exports, which dampen overall market bubbles. This makes the study of the oil and gas sector profoundly important for the political economy of Nigeria, as mediated by the NSM. Again, proxy variables that are heavily correlated with oil prices and key market fundamentals may come into such further work for example performance of Nigeria's Sovereign Wealth Fund (SWF) depends on oil prices and exchange rates.

For further investigation of NSM characteristics, in the next chapter we discuss the anomalies aspects of the Nigerian stock market.

CHAPTER 8: ANOMALIES STUDIES

8.1 Introduction

In finance, an anomaly typically refers to results that deviate from those expected under finance theory, in particular those related to the EMH. If the market is efficient, abnormal returns should not emerge when analysing and acting on publicly released information.

Stock market anomalies that are related to the calendar include the January effect, which finds that returns in the month of January are significantly higher than other months. The Monday effect finds that returns generated on Mondays are significantly negative and lower than other days of the week. This day-of-the-week effect extends to the observation that returns on Fridays are positive and higher than those of the rest of the week.

However, some major abnormalities have been detected in major capital markets around the world. Investors can earn abnormally high returns by using certain strategies derived from the observation of these irregularities. Some of these abnormalities have been persistent and of a large order of magnitude. Nobody fully understands why they exist, and therefore, they have been referred to as stock market anomalies. These anomalies point to two possible explanations, either the capital market itself is inefficient, or the current asset pricing model is miss-specified.

Because of the limitation of the data this study concentrates on the two most renowned anomalies namely the day-of-the-week effect and the monthly effect. This chapter tests the existence of these two anomalies on the NSM. Both parametric and non-parametric tests are used to test the significance of each effect individually. Moreover, each effect is tested on the whole period, as well as two sub-sample periods. The chapter aims to provide an answer for the research question 3 of this research:

RQ3: Are there any anomalies in the behaviour of the NSM data for example calender effects on the stock market returns?

8.2 Literature Review

As mentioned earlier, calendar effects are stock market anomalies which are related to the calendar, such as the (Monday) or day-of-the-week effect, the January effect or monthly effect, the pre-holiday effect and the intra-month effect, etc. Some of the common market anomalies are described below.

8.2.1 The Winner-Loser anomaly

This anomaly was first tested by De Bondt and Thaler (1985). They sorted the stocks in several groups. The best performing stocks were placed in the 'winner group' while the worst performing stocks were placed in the 'loser group'. The hypothesis they were trying to test was that if all the information is fully reflected in the current prices, then there should be no difference in the performance of different portfolios. The performance of the winner and loser groups was monitored over similar time period. They found evidence for short term persistence and long term reversals in stock returns. In other words, in the short term the loser portfolio performed worse but in long term the loser portfolio performed better than the winner portfolio. The findings confirmed the overreaction hypothesis which suggests that investors overreact to bad news compared to good news at least in short term, Damodaran (2002). As a result, over a long term we witness a reversal in stock returns as the investors accommodate the information accurately. This overreaction idea is also captured in GARCH models of volatility discussed in Chapter 9 of the thesis through model parameters which measure asymmetric effects of bad versus good news in financial markets.

However, there are some other anomalies at work in De Bondt and Thaler's work. For example, their results contain January anomaly with most of the loser portfolios registering most of their higher gains in the month of January. Also the gains of loser portfolios were significantly higher than the losses of winner portfolios which indicate asymmetry in price corrections. In addition, it is to be noted that De Bondt and Thaler did not notice the firm effect and it could be that their sample experienced firm-size anomaly as well. This size-effect was investigated further by De Bondt and Thaler in 1987 and they found that the winner-loser effect cannot be attributed to the size of the firms. They, however, explained that the winner-loser effect is mainly because of overvaluation of winner firms' stocks and undervaluation of the loser firm's stocks.

However, later studies found no evidence of winner-loser effect. In fact, Jagadeesh and Titman (1993) found that in contrast to what De Bondt and Thaler reported, winner stocks continue to outperform the loser stocks. There is, however, some confusion over the time period used by De Bondt and Thaler and Jagadish and Titman, because both suggested that in the short term winners outperform losers. The question is what we mean by short term here.

Market overreaction effect was also noted by Yulong et.al (2005) who concluded that markets generally reverse after a sharp rise or decline suggesting that at the first instance, market overreacts to good or bad news. One of the news that the market reacts to is earnings announcement. Abarbanell and Bernard (1992), on the other hand, reported that market underreacts to earnings announcement. Guin (2005) however, reports that stocks which report earnings considerably different from the consensus earnings forecasts tend to move by exceptional amounts. This price movement continues for up to several weeks after the announcement, meaning that an investor can still profit from the information, even though it has been made public. Similarly Fama (1997) reported Post-Earnings announcement drift effect which refers to the observation that in many cases markets continue their reaction to earnings announcement for periods lasting up to 1 whole year.

8.2.2 P/E Ratio (Price-Earnings Ratio) effect

This effect suggests that stocks with low P/E ratio are generally undervalued and thus generate higher than average market returns. Damodaran (2002) explain this and suggests that it could be because stocks with low P/E ratio tend to provide high dividend yields, which can contribute significantly to investors' tax burden. To avoid this, investors tend to avoid such stocks thereby resulting in their undervaluation.

8.2.3 Firm-size Effect

It is a general perception that small stocks tend to provide higher returns compared to larger firms with same beta, Damodaran (2002). It can be explained as follows:

- The transaction costs of investing in small stocks is comparatively higher and because investors expect return dependent on all costs added, expected returns on small firm stocks are higher. However, the transaction costs alone cannot explain the small firm effect, Damodaran (2002).

- CAPM model is not accurate and betas underestimate the correct risk associated with small firm stocks. The small firm effect is actually the readjustment of this beta to its accurate value. In other words, there is generally higher risk associated with small firm stock as compared to what is estimated using CAPM. Thus the excess returns earned by small firms are actually the returns associated with the gap in actual and estimated beta value (risk), Damodaran (2002).

8.2.4 The January Effect

Researchers have found overwhelming evidence that market returns vary according to the month of the year, practically the returns are higher during the month of January (Damodaran, 2002; Haugen and Jorion, 1996). However, January effect is related to small firm effect as most of the excess returns for small firms are earned in the month of January (De Bondt and Thaler, 1987). Keim (1983) estimated that small firms almost earn half of their excess returns during January.

Dimson (1988) provides one explanation for the observed January effect; he suggests that in December investors tend to sell off loser stocks and use the capital loss to offset any gains in taxable income. Due to massive sell off by several investors, the prices of these loser stocks are driven further down. Then in January, the investors return to the market to buy back the stocks. And because a lot of investors tend to buy at that time, the prices see a reversal in January (Damodaran, 2002). As expected on the basis of this explanation, the January effect is more prominent in the worst performing stocks. However, this explanation also links the January effect with the taxation policies of different countries because in some countries the taxation policies may not warrant the massive sell off in December or some countries may not have their financial year (related to taxation) ending in December. If Dimson's argument regarding tax loss prevention is correct then we must witness the same January effect in whichever is the financial year ending month in the country. For example, Australian year end for taxation purposes is June. But still in Australian stock market we can witness the January effect which contradicts Dimson's explanation.

This means that there must be another explanation for January effect. One possible explanation is towards the year end institutional investors tend to sell more and buy less while at the beginning of the year they reverse the trend by buying more and selling less. Because of the huge amount of shares traded by these institutional investors, we witness their buy and sell behaviour as January effect (Damodaran, 2002). However; Damodaran (2002) provides no empirical evidence in support of this explanation.

8.2.5 The Weekend Effect

As the name suggests this anomaly refers to the difference between returns on the first day of the week as compared to any other day of the week. Researchers (for example, Barone, 1990; French, 1980) have found that returns on the first day of the week are on average lower than the returns on any other day of the week. Furthermore, the weekend effect is comparatively more prominent in small firm stocks, Damodaran (2002).

Because the first day of the week is generally Monday, this effect is also known as Monday effect. However, in many Islamic states, Monday is not the first day of the week and hence it will not be correct to term the weekend effect as Monday effect. Nevertheless, it is termed as weekend effect because negative returns are shown towards close of business on Friday rather than towards Monday. One possible explanation for this could be that investors tend to settle what they consider risky positions in anticipation of bad news over the weekend. Guin (2005) suggests that "The weekend effect can be due to the fact that companies and governments tend to release bad news over the weekends".

One can argue that Monday effect could be because of investors waiting to adjust their position as quickly as possible following two days of non-trading. However; Damodaran (2002) argues that Monday effect cannot be attributed to the non-trading days (weekends) because on other days following the holidays stock markets generally register positive returns. If absence of trading is causing the Monday effect then we should witness similar effect following other holidays as well. But because it is not so, the non-trading days theory cannot be accepted.

Gibbons and Hess (1981) detected that Monday's returns are usually negative and lower than other days of the week. They used a regression-based test and found strong and persistent negative mean returns on Mondays for stocks during 1962 to 1978, and below-average returns for treasury bills on Mondays. Apart from that, they found that Tuesday's returns are slightly lower than average in general while Wednesday's and Friday's returns are slightly higher than average. All of these contributed to rejecting the view that mean returns on every day of the week are more or less the same. Their study also showed that all the stocks in the Dow Jones 30 for the overall period exhibited negative mean returns on Mondays. Moreover, T-bills also have the day of the week effect with Monday's returns lower, and Wednesday's returns higher, than the rest of the week. There are still no satisfactory explanations for these findings.

Keim and Starnbaugh (1984) also found a strong Monday effect, as with previous studies, but with no satisfactory explanations. In their study of a very wide period of 55 years (from 1928 to 1982), which also covered stocks from the Over-the-counter (OTC) market, the weekend effect is high throughout the whole period. During the first period 1928-1952, the stock market opened for trading on Saturdays which means that return on Mondays represented a one-day break instead of the usual two-day break which came later. The results from that period are still the same as the two-day weekends, but Friday's returns were lower on a one-day weekend, and Saturday's returns were higher. This indicates that the last price of the week, no matter which day, seems to be high. Moreover, Keim and Starnbaugh (1984) found that the Monday effect was high across firm-size deciles, but the smaller the firm, the higher Friday's returns. The measurement error was investigated in this study but with no satisfactory results.

Although the detected Monday anomaly and other patterns of day-of-the-week effects contradict the idea of market efficiency, recent results discovered a non-persistent effect in some sub-periods. Not finding a weekend effect in some periods does not argue that the market is efficient.

8.2.6 Long-term return anomalies

Researchers such as Fama (1998) investigated the market inefficiencies such as long term market overreaction and under-reaction. However, Fama refuses to reject EMH despite the evidence of long term overreaction and under-reaction. In support, he argues that if the under-reaction and over-reaction itself are randomly distributed then there is no reason for us to reject EMH. This random walk hypothesis is the key to EMH. In addition, the long term return anomalies are too dependent on the methodology adopted; some models may show strong evidence of such anomalies while in some other models these anomalies may fade or even completely disappear.

Market overreaction was studied by DeBondt and Thaler (1985) who provided empirical evidence of reversal of stock returns in long run indicating that market initially overreacts to any good or bad news and readjusts to equilibrium stage. The argument regarding overreaction confirms the behaviour theory proposed by Kahneman and Tversky (1982). Explaining this further Lakonishok et al. (1994) suggests that firms with high performance ratios tend to have poor past earning growth and vice versa. This, he explains, is because of market's overreaction and behavioural trading where invertors ignore the mean reversion of return and expect the stock to continue to perform in near future. As a result many investors buy when the stock prices are rising and sell when stock prices are declining thereby making an overall loss.

8.2.7 IPOs (Initial Public Offering) anomalies

There are quite mixed comments on IPO anomaly. For example, Raghuram and Servaes (1997) suggest that "analysts are overoptimistic about the earnings and growth performance of IPO's". McNichols and O'Brien (1996) explain that this over optimism may be a result of selection bias; "analysts typically start following stock they are optimistic about". This over optimism can often lead to overpricing. If this is true we must witness poor returns on stocks after IPO. In fact, Ritter (1991) found that in the long run, after 3 years of going public, firms significantly under performed as compared to the market.

But, on the contrary, Jong-Hwan (2003) suggests that there exist evidence of an under-pricing phenomenon of IPO's which results in positive average abnormal return found over a short period of time after the issue. Combining these evidences, it can be suggested that immediately after the IPO and in the short run stocks perform better than the market but like in most cases, prices mean revert and hence in the long run, these stocks underperform as compared to market. This once again confirms that investors do engage in behavioural trading (for example, overreaction).

8.3 Adopted Method for seasonality and calendar effects

Seasonality or calendar effects are used as evidence of failure of EMH. Existence of this effect means that investors can invest in time research and make abnormal gains. In this research two calendar effects are examined; the day-of-the- week effect and January effect.

In order to test daily and monthly effects, parametric and non-parametric tests are used to test hypotheses comparing means of two or more groups. The assumption of the parametric test is that the data are normally distributed while the assumption of the non-parametric is that the distribution of the data is non-normal or unknown. In this chapter

ANOVA tests are used as parametric tests while the Kruskall-Wallis test will be used as non-parametric test. The idea behind using both examinations parametric and non-parametric tests is that the normality test cannot be denied for pre-reform phase using monthly data whilst we reject the normality for other phases.

For daily effect the hypothesis is $H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ where $\mu_1, \mu_2, \mu_3, \mu_4 and\ \mu_5$ are the mean return for Monday, Tuesday, Wednesday, Thursday and Friday respectively. The null hypotheses for monthly effect is $H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_6 = \mu_7 = \mu_8 = \mu_9 = \mu_{10} = \mu_{11} = \mu_{12}$ where $\mu_1 \ldots \mu_{12}$ are the average return for the months January to December respectively.

8.3.1 Parametric Tests

The parametric test is used to test hypotheses under the assumption that the data are normally distributed. The parametric test used in this chapter is the Analysis of Variance (ANOVA). The variance s^2 is computed as follows:

$$s^2 = \frac{\sum_i (x_i - \bar{x})^2}{n-1} \qquad \text{Equation 8-1}$$

8.3.2 Non-Parametric Tests

Kruskall-Wallis H-test (for *k* independent samples)

Kruskal-Wallis is also known as the Kruskal-Wallis H test. According to Bryman and Cramer (2001), it is a non-parametric test similar to the Mann-Whitney U test. However, Pallant (2007) noted that it helps to compare more than two independent groups. Where as Cooper and Schidler (2006) described it as a generalized version of the Mann-Whitney U test.

The Kruskall-Wallis H-test is for use with *k* independent groups, where *k* is equal to or greater than 3. The null hypothesis is that the *k* samples come from the same population, or from populations with identical medians. However, because the samples are independent, they can be of different sizes.

The statistic H is given by:

$$H = \left[\frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i}\right] - 3\,(N+1) \qquad \text{Equation 8-2}$$

where k = the number of independent samples; n_i = the number of cases in the i^{th} sample, N = the total number of cases, R_i = the sum of the ranks in the i^{th} sample and $H \sim \chi^2(k-1)$

8.4 Data

The daily and monthly returns on the NSM index, during the period from 3rd January 2000 to 31st December 2010, used in the analyses are as described in chapter 5.

Continuously compounded returns on the NSM index are calculated on a daily and monthly (end-of-month) basis, by using the following formula

$$R_t = \ln\left(\frac{I_t}{I_{t-1}}\right) \times 100 \qquad \text{Equation 8-3}$$

Where R_t return on the NSM index at time t, I_t NSM index at close of time t and I_{t-1} NSM index at close of time t- 1

However, in the case of a day following a non-trading day, we calculate the return by using the closing price indices of the last trading day. To test the month of the year effect or January effect on adjusted returns the typical model that is quite similar to seasonal daily anomalies were used.

The full-sample is divided into three sub-periods. The first is the entire period from January 2000 to December 2010. The second and third sub-periods are from January 2000 to December 2004 and from January 2005 to December 2010, respectively (pre- and post-reforms.

Total number of observations and summary statistics are given in Table 8.1 as follows.

Table 8-1 : Summary Statistics for NSM returns during the periods of study

Variables	All Period 2000 - 2010	Pre-reforms 2000 - 2004	Post-reforms 2005-2010
Daily Data			
Mean	0.0599	0.1341	0.0026
Median	0.0000	0.0707	-0.0003
Maximum	7.0631	7.0631	3.8433
Minimum	-7.2320	-7.2320	-4.6673
Std. Dev.	1.0713	1.0388	1.0926
Skewness	-0.0194	-0.0623	0.0240
Kurtosis	6.3999	9.3253	4.5857
Jarque-Bera	1248.559	1884.504	153.3081
Probability	0.0000	0.0000	0.0000
Sum	155.3314	151.5213	3.8101
Sum Sq. Dev.	2973.403	1218.196	1744.188
Observations	2592	1130	1462
Monthly Data			
Mean	0.1833	2.5396	0.0529
Median	0.7345	2.5529	-0.1377
Maximum	3.5614	2.3418	3.5614
Minimum	-3.1757	-2.5905	-3.1757
Std. Dev.	7.6646	5.5394	8.9465
Skewness	-0.6374	-0.1428	-0.4788
Kurtosis	8.6538	3.0649	7.9139
Jarque-Bera	184.7484	0.2146	75.1914
Probability	0.0000	0.8983	0.0000
Sum	23.4212	2.7861	20.6351
Sum Sq. Dev.	140.4095	48.9398	89.5821
Observations	132	60	72

Table 8.1 shows that, for the daily data the average return of the NSM index for the entire period is 0.06% per day with standard deviation of 1.07. The data have very high kurtosis but they are not much skewed.

The overall and post-reforms periods have a mean return of 0.05% and 0.003% which are not statistically different than zero. However, the pre-reforms period has an average return of as much as 0.13% per day which is very significantly different from zero. As it has been discussed early in chapter five slightly deferent results can be read for the monthly data. High volatility been reported in all three periods of the study when monthly data were used. The P-value for pre-reforms period changed from 0.0000 when daily data used to 0.8983 when monthly series applied. The Jarque-Bera test and the P-value suggest that both monthly and daily data are not normally distributed during overall and post-reform periods, while the normality hypothesis cannot be rejected for the pre-reforms period using the monthly data series, thus both parametric and non-parametric test will be conducted to test day of the week and monthly effect on NSM returns. From more about normality test refer to chapter Five.

8.5 Empirical Results

8.5.1 The day of the week Effect

Table 8.2 display the descriptive statistics for each day of the week. The last Column of the table is returns for all the days of the week except Monday in order to compare the average returns and attempt to establish the Monday effect.

Table 8-2 : Summary Statistics for Each Group of Data by days

Variables	Monday	Tuesday	Wednesday	Thursday	Friday	Week days Except Monday
All Period 2000 – 2010						
Mean	0.1133	0.0363	-0.0298	0.0762	0.1017	0.0478
Median	0.0000	0.0000	-0.0003	0.0456	0.0212	0.0000
Maximum	7.0631	5.7221	3.3450	3.8284	3.9333	5.7221
Minimum	-3.6211	-3.7222	-4.0584	-3.8143	-7.2320	-7.2320
Std. Dev.	1.1066	1.0936	1.0518	1.0680	1.0514	1.0619
Skewness	0.7000	0.2726	-0.2980	-0.0727	-0.8897	-0.2233
Kurtosis	7.0414	5.1593	5.0829	4.8674	9.9259	6.1593
Jarque-Bera	386.4412	106.8389	104.6315	76.7408	1090.8750	887.4215
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	57.4300	18.7845	-15.9274	40.0294	52.0742	100.0681
Sum Sq. Dev.	619.6592	617.1285	590.7475	597.6419	564.8300	2358.051
Observations	507	517	535	525	512	2092
Pre-reforms 2000 – 2004						
Mean	0.1636	0.1805	0.0452	0.1947	0.0908	0.1285
Median	0.0564	0.1058	0.0144	0.1336	0.0055	0.0729
Maximum	7.0631	5.7221	3.3301	3.3615	3.9333	5.7221
Minimum	-3.6211	-2.9292	-4.0584	-3.8143	-7.2320	-7.2320
Std. Dev.	1.1116	1.0611	1.0518	0.9889	1.0602	1.0201
Skewness	1.0639	0.6336	-0.5628	-0.0942	-1.7041	-0.4298
Kurtosis	10.0515	6.7420	6.3088	5.1631	15.6396	8.9644
Jarque-Bera	508.6100	143.7219	118.5897	45.1813	1585.220	1370.829
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	36.8136	39.8808	10.5377	44.7893	20.1669	116.3811
Sum Sq. Dev.	276.7886	247.7111	231.8431	223.9535	248.4153	941.7551
Observations	225	221	233	230	222	906

Post-reforms 2005-2010						
Mean	0.0731	-0.0713	-0.0876	-0.0161	0.1100	-0.0138
Median	-0.0003	-0.0004	-0.0023	0.0000	0.0252	-0.0003
Maximum	3.8433	3.5059	3.3450	3.8284	3.6021	3.8284
Minimum	-3.1104	-3.7222	-3.5862	-3.7051	-4.6673	-4.6673
Std. Dev.	1.1030	1.1068	1.0884	1.1187	1.0463	1.0892
Skewness	0.4046	0.0674	-0.1164	-0.0081	-0.2416	-0.0749
Kurtosis	4.4922	4.0529	4.4506	4.6989	5.2746	4.5792
Jarque-Bera	33.8549	13.8970	27.1602	35.4791	65.3368	124.3464
Probability	0.0000	0.0010	0.0000	0.0000	0.0000	0.0000
Sum	20.6164	-21.0963	-26.4651	-4.7599	31.9073	-16.3130
Sum Sq. Dev.	341.8454	361.3996	356.5828	367.9416	316.3684	1405.909
Observations	282	296	302	295	290	1186

For the entire period, Monday's mean of 0.11% is higher than 0.04% generated from other days. However, the mean of both Monday and other all day's returns are significantly different from zero. While returns on Monday are greater skewed at 0.70% compared with -0.22% for other day, Kurtosis for both periods Monday and other days are quite similar; 7.04% for Monday and 6.16% for other days.

During the pre-reforms period, mean returns for Monday and other days are positive. Both groups have high kurtosis; 10.05% for Monday and 8.96% for other days. Returns for Monday are significantly positive skewed at 1.06%, while returns for other days are negatively skewed at -0.43%. It is noticeable that average returns on both groups are slightly higher than in the overall period.

During the post-reforms period, average return on Mondays of 0.07% is higher than average return on other days by around 0.07%. With almost same kurtosis in both groups; the kurtosis during this period is less than the kurtosis in the first two periods. Positively skewness reported during this period on Mondays but not as much as the first two periods, while same as the first two periods negatively return was reported during the other days but with less skewness at -0.07%. All the groups have high standard deviation which reflects the fluctuating period in the NSM market.

8.5.2 Results for the Parametric Test

In order to gain more insight into the detected Monday effect in general and to attempt to detect other possible day-of-the-week effects which might exist on the NSM, same analysis were applied on same data for each working day of the week. The descriptive statistics for each day of the week are given in Table 8.2.

During the entire period of the study, with almost same standard deviation for all days, Monday has the highest mean of 0.1133 per day and Wednesday has the lowest mean, (-0.0298) and is the only day that has a negative mean among all the days. Mean return for all days during this period is 0.05. High skewness statistics are reported for daily with positive skewness for Monday and Tuesday and negative skewness for other days. All the days have very high kurtosis.

The pre-reforms period has a higher overall average return (0.13%) than all and post-reforms period. With a positive mean return for all day of the week Thursday has the highest mean of return with 0.19% which is higher by 0.06% from overall period. The lowest average return during this period is 0.05% which recorded on Wednesday. The standard error for all the days and for overall period is almost same at 1.1%.

The overall average return for post-reforms is very low at 0.0026 which is not statistically different from zero. Friday records the highest mean return during this period at 0.11%. Again as in the previous period Wednesday has the lowest return of as much as -0.08%. The overall mean return during this period is negative at -0.01%. Both Monday and Friday have positive average return where Tuesday, Wednesday and Thursday have negative return. Parametric test for the three periods are presented in the following section.

8.5.2.1 The ANOVA test

The ANOVA test used to compare variances of number of groups in order to find out whether or not the averages of the groups are statistically same. In other words the test aims to test the following hypothesis:

$H_0: \mu = \mu_1 = \mu_2 = \mu_3 = \mu_4$

Where μ is average of returns on Mondays, μ_1, μ_2, μ_3 and μ_4 are average of returns on Tuesday, Wednesday, Thursday and Friday respectively.

Table 8.3, Table 8.4 and Table 8.5 shows the ANOVA test (Comparing Mean Returns on all working days of the week) for all the three periods of the study, overall, pre-reforms and post-reforms.

Table 8-3 : The ANOVA Test for Overall period (2000 – 2010)

Returns

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6.724	4	1.681	1.466	.210
Within Groups	2966.679	2587	1.147		
Total	2973.403	2591			

Table 8-4 : The ANOVA Test for Overall period (2000 – 2004)

Return

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.692	4	.923	.855	.490
Within Groups	1214.504	1125	1.080		
Total	1218.196	1129			

Table 8-5 : The ANOVA Test for Overall period (2005 – 2010)

Return

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.927	4	2.232	1.874	.113
Within Groups	1735.261	1457	1.191		
Total	1744.188	1461			

For the overall period, the table above indicates that average returns on different days of the week are not statistically different from each other, with F statistics of 1.466 which is not significant at least at the 5% level.

Results for pre-reforms period show the mean return on days of the week are not significantly different from each other, with F ratio 0.855. For the third period, with F ratio 1.874 which is not significant, returns generated from different day of the week are not significantly different from each other.

ANOVA test shows that there is no a day of the week effect exists in the three periods of study using daily data.

8.5.3 Results for Non-Parametric Test

The test aims to test the following hypothesis:

$H_0: \mu = \mu_1 = \mu_2 = \mu_3 = \mu_4$

Where μ is average of returns on Mondays, μ_1, μ_2, μ_3 and μ_4 are average of returns on Tuesday, Wednesday, Thursday and Friday respectively.

Table 8.6, Table 8.7 and Table 8.8 show Kruskal-Wallis test for NSM return for the three periods under study.

Table 8-6 : Kruskal-Wallis test for daily data (2000-2010)

Days	Mean Rank	Chi-square	df	Sig.
Mon	1305.68	7.023	4	.135
Tue	1275.51			
Wed	1237.16			
Thu	1313.58			
Fri	1353.03			

Table 8-7 : Kruskal-Wallis test for daily data (2000-2004)

Days	Mean Rank	Chi-square	df	Sig.
Mon	561.05	2.505	4	.644
Tue	577.67			
Wed	544.12			
Thu	587.36			
Fri	557.73			

Table 8-8 : Kruskal-Wallis test for daily data (2005-2010)

Days	Mean Rank	Chi-square	df	Sig.
Mon	746.39	9.698	4	.046
Tue	703.66			
Wed	690.03			
Thu	732.12			
Fri	787.86			

Table 8.6 reported that there was no statistically significant difference between the different daily returns (Chi-square = 7.023, $P = 0.135$) with a mean rank of 1305.68 for Mondays, 1275.51 for Tuesday, 1237.16 for Wednesday, 1313.58 for Thursday and 13.53.03 for Friday, thus, we fail to reject the null hypothesis. This conclusion is

consistent with the finding of the parametric test. Same conclusion for the post reforms period can be read from Table 8.7 where Chi-square = 2.505 and P-value = 0.644.

Table 8.8 show a different result from parametric test for the post reforms period. While for the parametric test we accept fail to reject the null hypothesis, non-parametric test suggested rejection for the null hypothesis at 5% level (Chi-square = 9.698, P-value =0.046).

Results for studying the effect of the day-of-the-week in the three sub-periods showed that no significant day of the week effect on the NSM during the three periods as a result of the parametric test. However, results for non-parametric test show same result for both overall and pre-reforms periods. The non-parametric test for post-reforms period, however, showed a day of the week effect with a small significance which is different from the finding of the ANOVA test. This difference may be due to low statistical power from reduced sample size.

For the NSM, it can be concluded that there are no day-of-the- week effects. These findings are supported by a number of studies in the field such as Basher and Sadorsky (2006) who use both unconditional and conditional risk analysis to investigate the day-of-the-week effect in 21 emerging stock markets. The results in the study show that while the day-of-the-week effect is not present in the majority of emerging stock markets studied, some emerging stock markets do exhibit strong day-of-the-week effects.

8.5.4 The Month of the year Effects (The January Effect)

The literature shows that developed stock markets returns in the month of January are significantly higher than the rest of the year. In the following sections the January effect of NSM is investigated.

In order to investigate whether there are any monthly effects on NSM return, the return for each month of the year during the same periods of study are compared against each other by using both parametric and non-parametric tests. The aim is to test whether there are a statistically difference between the mean of the returns for each months. In other word, the following hypothesis will be tested:

$H_0 = \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_6 = \mu_7 = \mu_8 = \mu_9 = \mu_{10} = \mu_{11} = \mu_{12}$

Where; μ_1 to μ_{12} are average return form January to December.

Before conducting the tests general characteristics of the data been looked at by investigating the descriptive statistics for the three periods of the study for January and other months. The results for the three periods are reported in Table 8.9, Table 8.10 and Table 8.11.

Table 8-9 : Descriptive Statistics for each month of the year for overall period (2000-2010)

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
January	1.2690	8.0871	13.8121	-2.0175	6.3136	12.4951	0.0019
February	4.2501	3.7616	5.1016	-0.0944	2.1460	0.3506	0.8392
March	-1.2661	-1.0125	8.0247	-0.1237	2.7226	0.0633	0.9688
April	3.1742	1.6327	5.3214	0.0806	2.1775	0.3220	0.8513
May	5.4942	4.3395	9.5721	2.1722	7.0037	15.9971	0.0003
June	1.7345	3.3460	5.7093	-0.8619	2.6504	1.4181	0.4921
July	-0.5027	0.1414	4.8078	0.1687	1.6183	0.9272	0.6290
August	-0.6528	-1.7579	9.6682	0.4956	2.1059	0.8167	0.6648
September	-1.2945	-1.6506	3.8692	1.1314	3.1960	2.3646	0.3066
October	0.9925	1.5822	9.6749	-1.4951	5.3840	6.7028	0.0350
November	-1.1382	-1.1144	4.9260	0.1981	2.5115	0.1813	0.9133
December	2.1394	1.1104	4.8737	0.7729	3.1782	1.1097	0.5742

Table 8-10 : Descriptive Statistics for each month of the year for pre-reforms period (2000-2004)

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
January	7.2333	8.6775	5.8721	-1.2352	2.9375	1.2723	0.5293
February	4.1484	3.7616	3.9778	0.6013	2.5842	0.3373	0.8448
March	-0.9228	0.1660	5.6633	-0.6339	2.5829	0.3711	0.8306
April	3.2969	1.6327	5.5866	0.8948	2.4076	0.7404	0.6906
May	4.2855	4.3395	2.4470	-0.2978	2.0448	0.2640	0.8764
June	5.7512	5.9132	2.0229	-0.0923	1.3757	0.5567	0.7570
July	-1.4759	-3.3554	5.0566	0.7707	2.2745	0.6046	0.7391
August	0.5557	-1.0514	9.4007	-0.2913	2.0019	0.2783	0.8701
September	-1.3868	-1.2959	3.5135	0.8019	2.3671	0.6193	0.7337
October	4.5551	2.6691	6.5018	0.3890	2.0028	0.3333	0.8465
November	0.6756	0.7026	3.3167	0.0936	2.3158	0.1048	0.9489
December	3.7608	2.4367	5.5283	0.8876	2.5741	0.6944	0.7067

Table 8-11 Descriptive Statistics for each month of the year for post-reforms period (2005-2010)

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
January	-3.7013	-0.3529	16.9925	-1.3868	3.5356	1.9950	0.3688
February	4.3348	4.3166	6.2749	-0.2533	1.7468	0.4568	0.7958
March	-1.5522	-3.1222	10.1448	0.0235	2.1409	0.1851	0.9116
April	3.0719	4.1940	5.6248	-0.5414	1.8925	0.5998	0.7409
May	6.5016	2.4597	13.2583	1.4678	3.6174	2.2497	0.3247
June	-1.6128	-1.3576	5.6867	-0.2373	1.9262	0.3446	0.8417
July	0.3083	1.7453	4.9030	-0.3163	1.6527	0.5539	0.7581
August	-1.6598	-5.8405	10.6570	1.0078	2.5544	1.0652	0.5871
September	-1.2177	-2.4989	4.4778	1.1982	3.1321	1.4400	0.4867
October	-1.9763	0.1096	11.4070	-1.3836	3.5731	1.9964	0.3685
November	-2.6497	-3.4290	5.8050	0.8165	2.8748	0.6707	0.7151
December	0.7882	-0.4258	4.2704	0.2391	1.8802	0.3706	0.8308

For the entire period, May has the highest average monthly return at 5.50% per month comparing to other months. The lowest average return for the same period recorded in September with -1.30% average returns per month. Negative average returns are reported for five months namely March, July, August, September and November while the rest reported positive return.

During the first sub-period, the highest average returns recorded in January (7.2%) while May reported the highest average of returns during the second sub-period. comparing the two periods, the lowest mean return reported in July for the first sub-period and in November during the second sub-period. The negative average return increased from 3 months during pre-reforms period to 7 months during post reforms period and this may be as a result of the global financial crises.

8.5.5 Parametric test

8.5.5.1 ANOVA Test

Table 8-12 The ANOVA Test for Overall period (2000 – 2010)

Monthly Return

	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	626.528	11	56.957	.967	.480
Within Groups	7069.146	120	58.910		
Total	7695.674	131			

Table 8-13 The ANOVA Test for pre-reforms period (2000 – 2004)

Monthly Return

	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	475.239	11	43.204	1.553	.144
Within Groups	1335.163	48	27.816		
Total	1810.402	59			

Table 8-14 The ANOVA Test for post-reforms period (2005 – 2010)

Monthly Return

	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	630.331	11	57.303	.680	.751
Within Groups	5052.543	60	84.209		
Total	5682.874	71			

Results for overall period from the above tables show no significance at 5% level. This indicates that the mean returns in each months of the year are not significantly different from each other. Thus, the results suggest that the null hypothesis is not rejected. Results from tables above also confirm the insignificance of the month of the year effect in both pre and post reforms periods at 5% level.

The results contradict previous research done on other developed stock markets because there is no January anomaly on NSM. Return on January months are not significantly different from the other months. Therefore, further investigation to examine whether or not there is any other possible monthly effect on NSM conducted using the regression model.

8.5.5.2 Non- Parametric test

Table 8.15, Table 8.16 and Table 8.17 shows the results for non-parametric tests from the three periods under the study using Kruskal-Wallis test.

Table 8-15 Kruskal-Wallis test for Monthly data (2000-2010)

Days	Mean Rank	Chi-square	df	Sig.
Jan	81.55	17.120	11	.104
Feb	85.00			
Mar	53.55			
Apr	78.45			
May	82.36			
Jun	71.55			
Jul	53.45			
Aug	53.09			
Sep	45.45			
Oct	73.09			
Nov	50.09			
Dec	70.36			

Table 8-16 Kruskal-Wallis test for Monthly data (2000-2004)

Days	Mean Rank	Chi-square	df	Sig.
Jan	45.20	17.152	11	.103
Feb	35.20			
Mar	21.60			
Apr	32.00			
May	38.00			
Jun	43.00			
Jul	16.80			
Aug	26.60			
Sep	15.20			
Oct	35.60			
Nov	23.80			
Dec	33.00			

Table 8-17 Kruskal-Wallis test for Monthly data (2000-2004)

Days	Mean Rank	Chi-square	df	Sig.
Jan	38.00	9.508	11	.575
Feb	50.00			
Mar	31.33			
Apr	46.50			
May	45.50			
Jun	31.33			
Jul	36.83			
Aug	25.50			
Sep	30.67			
Oct	38.00			
Nov	25.83			
Dec	38.50			

Above tables show that, for the overall periods the significance level of approximately 0.104 and the chi-square statistics of about 17.120 indicates the insignificance of the results in the non-parametric test which confirm the result of the parametric test. This means that there seems to be no difference between returns of any month of year during overall period.

There also seems to be no statistical difference in average returns between each month of the year during pre-reforms period according to non-parametric test. This conclusion supported by parametric test. Kruskall-Wallis test confirm the insignificance with a chi-square statistics of 17.152 and significance level of 0.103.

No significance monthly effect in the third period also. The non-parametric test display insignificant results with a chi-square 9.508 and significance level of 0.575.

In summary, the non-parametric test suggests that no monthly effects on the NSM during any of the three periods. This finding is constant with the ANOVA test finding.

8.6 Summary and Discussion

This chapter tests the two major calendar effects, namely day-of-the-week effect and monthly effect on Nigerian stock market in order to answer research question 3 of this work.

RQ 3: *Are there any anomalies in the behaviour of the NSM data for example calendar effects on the stock market returns?*

8.6.1 Anomalies in the Nigerian Stock Market

Traditionally, business and financial activities have a slow start on Monday since all financial intermediaries, stock market, and other organizations are closed on Saturday and Sunday. This pause produces an inertia effect and slow start on Mondays as well as quiet space where information such as bad news occurring during the weekend may have more effect on the Monday performance than might have occurred during the busy work week, Islam and Watanapalachaikul (2005).

8.6.2 Discussion

This chapter tests the two major calendar effects, namely day-of-the-week effect and monthly effect on Nigerian stock market. As for day-of-the-week effect, this study found no significant daily effect on NSM using both parametric and non-parametric tests, which means no Monday effect as well. This finding is supported by Ajayi et al. (2004) who conducted an empirical investigation of the day-of-the-week stock return anomaly using major market stock indices in eleven Eastern European Emerging markets (EEEM). Their findings provide no consistent evidence to support the presence of any significant daily patterns in the stock market returns of the EEEM.

Aly et al. (2004) investigates daily stock market anomalies in the Egyptian stock market, the results indicate that Monday returns are not significantly different from returns of the rest of the week. Thus, no evidence was uncovered to support any daily seasonal patterns in the Egyptian stock market. Raj and Kumari (2006) concluded their study by that the negative Monday effect and the positive January effects are not found in India Stock Market.

The finding is also supported by recent studies based on data from non-African emerging markets (Asian and European) such as Ullah et al. (2010) who studied Pakistani stock market, and Depenchuk et al. (2010) who investigated Ukrainian financial markets.

We remark that even though the daily effects were not significant overall as noted, there is some indication that there could be daily effects in the market as shown by the Kruskall-Wallis test for daily data for the period 2005-2010 (post-reform period) ($p = 0.046 < 0.05$). This shows that the financial reforms and possibly the global financial crisis appear to have introduced market anomalies in the form of daily effects. This result is confirmed in the volatility tests in Chapter 9 of this thesis.

Also, the fact that we observe significant daily effects in the 2005-2010 period but not similar monthly effects (anomalies) suggests that the effects of the bank reforms and global financial crisis may suffer from time aggregation problems in financial and econometric modelling, whereby effects reported at lower levels of data in a study (for example, daily) may fail to exist at higher levels of data (for example, weekly or monthly). In addition, these effects are studied in this thesis at overall market level, at which they may be masked by the counteracting influences of different sectors. This means that further work is required to explore possible time aggregation problems in the NSM and model all the market characteristics in the thesis (hence the anomalies in NSM returns in this chapter) at sector- and company-specific levels. We have pointed out in previous chapters the need to focus the market characterisation work on key sectors of the Nigerian financial markets (for equities, bonds and money markets) for example oil and gas, banking and financials, telecommunications, agriculture, and manufacturing.

It is also known that in some financial markets information is released about the middle of the week, for example, Wednesday. This makes such days information rich compared to other days, just as weekends are typically less information rich due to absence of market activity during the weekends. Similar monthly effects can also result from differences in annual reporting cycles for example March-April in UK and August-September or December-January in other countries. Consequently, we need to explore on which days information are typically released in the Nigerian financial system by such organizations as the CBN, the SEC and NSE, et cetera. This knowledge will help provide better intuitive interpretations of observed daily and/or monthly anomalies.

It is instructive that the manner in which anomalies, bubbles and volatilities in financial markets play out depends to a large extent on the transmission of information through the markets, especially the reaction of market participants to new and old information. This forges a link among anomalies, bubbles, volatilities and behavioural finance/economics which we examine further in our notes on the implications of the research results from this thesis for welfare economics and stock market development in Chapters 9 and 10 of the thesis.

Average returns for each 12 months were compared against each other in order to investigate the existence of the monthly effect on NSM. The study found no significance between return in each month using parametric and non-parametric test. Therefore, according to this aspect, there is no monthly effect on NSM. Some previous studies support our findings. Joshi et al. (2006) examined the phenomenon of monthly effect empirically in the Nepalese stock market from February 1, 1995 to December 31, 2004 covering approximately ten years. Using regression model with dummies, they found no evidence of month-of-the-year effect. Agathee (2008) examined possible month of the year effect in an emerging market, in particular, the Stock Exchange of Mauritius (SEM). The equality of mean-return tests shows that returns are statistically the same across all months.

With respect to the link between the results in this chapter and the objectives and research questions we set out to explore in the thesis, we state as follows.

The chapter critically reviews the literature base on applied statistical models typically used in the study of market anomalies, in order to enable future researchers to benefit from using such models in related work (**Objective 1**). This literature will also guide future work on anomalies at sector- and company-specific levels. Similarly, it is known in the literature that techniques such as OLS can be employed to investigate anomalies especially when additional variables from both the macro-economy and sectors and companies are available, Islam and Watanapalachaikul (2005). This technique could therefore be employed in future studies in addition to other suitable models (**Objective 2**).

In terms of the policy implications of the results (**Objective 3**), we note that knowledge of the existence of market anomalies will help investors to determine how to realise high returns in the NSM especially given the fact that the market is weak-form inefficient. But it should be noted that for investors to actually achieve this objective they should weigh the effects of transaction costs for setting up the investment schemes on net gains from the investments, and also conduct proper fundamental analysis (valuations) of market assets and portfolios.

From the perspective of policy makers, knowledge of market anomalies and also other market imperfections discussed in Chapters 2-9 of the thesis, enables them to plan effective interventions in the market aimed at improving stock market performance, stock market development, financial reforms and policies, and overall economic development of Nigeria. For example, if some days or months are clearly anomalous, then the CBN, SEC and NSE will attempt to make market and financial reporting regulations that will reduce the anomalies.

For further investigation of NSM characteristics, in the next chapter we discuss the volatility aspects of the Nigerian stock market.

CHAPTER 9: VOLATILITY STUDIES

9.1 Introduction

Following the 2004 bank restructuring, related financial reforms in Nigeria, and the 2007-09 global financial crisis, the Nigerian financial market has experienced near bank failures which were prevented by proactive interventions by the Central Bank of Nigeria (CBN). There has also been a dramatic fall (more than 60%) in the market capitalisation of the Nigerian Stock Market (NSM) between 2008 and 2009, in addition to relatively wilder fluctuations in exchange rate of Nigeria Naira compared to international currencies for example US Dollar and UK Pound Sterling. Indeed, while this thesis was being developed the Naira has declined in value from about N252 to N260 to the US Dollar. These fluctuations inform similar fluctuations in the NSM All Shares Index and returns, making the study of volatility in NSM returns topical, especially in light of structural and operational characteristics of the market and wider implications for political economy concerns for example investment and risk management, financial policy and economic development, and stock market development, linked to GDP growth, competitiveness, market microstructure, and macroeconomic policy setting, African Development Bank (AFDB, 2007), Roubini and Setser (2004), Fong and Koh (2002), Osinubi (2004), Poon and Granger (2003), Ezepue and Solarin (2008), Schwert (1990), Islam and Watanachalapaikul (2005, p. 123-153), Li (2007), Au-Yeung and Gannon (2004) and McMillan et al (2000).

The study of volatility is interestingly controversial when viewed from a number of perspectives including: comparative model performances amongst classes of volatility models and different models within a given class; how well the models approximate the true generating stochastic process for observed or implied volatilities; ability of the models to capture the stylized facts of volatility in global financial markets for example asymmetrical effects of negative and positive news, volatility clustering, and volatility persistence, Wong and Cheung (2010), Poon and Grange (2003), Engle and Ng (1993); incorporation of variables other than historical records of returns in volatility analyses, for example, use of dummy variables to include the effects of days, months, years, interest rates, trading volume, Islam and Watanachalapaikul (2005), Wong and Cheung (2010); key issues in volatility forecasting versus explanatory modelling for example choice of lags and model specification problems; and multicollinearity among independent variables, Poon and Granger (2003) and other references therein.

Pertinent questions in volatility modelling therefore include: whether the stock market is excessively volatile or not; correct choice of models that match the stylized facts of the financial quantities modelled; frequency and spacing of underpinning data for example use of intra-day, weekly, daily or monthly data; and appropriate size of data suitable for one period or k-period ahead forecasts, in case of volatility forecasting, or for maximal model power in case of explanatory volatility modelling which is the focus of this chapter. We explore some of these questions in this chapter and justify our focus on Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models as opposed to, say, Autoregressive Conditional Heteroskedasticity (ARCH) and Stochastic Volatility (SV) models.

Volatility modelling in emerging markets is of increasing interest to (international) investors, financial institutions, policy makers and academics for different and sometimes related reasons, Aggarwal et al (1999), De Santis and Imrohoroglu (1997), Haque et al (2001, 2004), Islam and Watanapalachaikul (2005), Li (2007), Fong and Koh (2002), Batra (2004) and Liu and Morley (2009). Investors search for arbitrage opportunities which, though fundamentally connected to the degree of inefficiencies in a market, have fingerprints in the observed or implied volatilities associated with key financial quantities and their derivatives. Examples of these financial quantities are stock volumes traded across specified periods, market capitalisation, stock market indexes, interest rates, exchange rates, options, futures, and commodity prices for example oil prices in Nigeria, which correlate with key financial quantities given the country's heavy dependence on oil revenues. Also a good understanding of volatility is important for stock market investors since high volatility means high risk and uncertainty and therefore signals potentials for excessive gains or losses, Islam and Watanachalapaikul (2005).

Policy makers need to understand the volatilities in the financial system at overall market and sector-/company-specific levels, in order to gear monetary, macroeconomic and fiscal policies towards enhancement of economic performance, GDP growth, competitiveness and asset price stability. Stock market policy makers particularly need this understanding for effective stock market development. Academics study volatilities for all these reasons from a utilitarian viewpoint and to contribute academically to the literature on volatility modelling and financial market analyses in such fields as empirical finance, financial economics, investment and financial risk management, and financial engineering.

Despite this increasing interest in volatility research on emerging markets, the literature on volatility modelling in emerging African markets is relatively sparse; it is sometimes shrouded in related work on market efficiency, bubbles and anomalies and, with few exceptions on papers with an economic development thrust, seems to concentrate mainly on the academic interest of the authors as opposed to stock market characterisation and development, Chinzara (2008), Chukwuogor (2008), Jefferis and Smith (2005), Mecagni and Sourial (1999), Dickinson and Muragu (1994). Chinzara (2008) is particularly instructive for this chapter since it studies long-run comovement, dynamic returns linkages and volatility transmission between the world major and South African stock markets, but it does not address gaps in volatility studies mentioned here, because South African stock markets are more closely aligned to UK financial markets, whilst this research focuses on emerging African markets south of the Sahara. Chinzara (2008) reinforces the emphasis of the research on stock market characterisation through a detailed understanding of market-level volatility and its subtle links with other key market characteristics for example efficiency, bubbles, anomalies, predictability, and valuation of asset prices and returns, Ezepue and Solarin (2008).

In sum, this chapter elucidates the important theoretical and practical issues associated with ARCH/GARCH modelling with a special focus on:

a) identification of suitable volatility models for the NSM and other sub-Sahara African markets;
b) implications for stock market characterisation research and development, and welfare economics of the Nigerian financial system (institutions and policies), within a changing global financial architecture, Islam and Watanalapalachaikul (2005), Ezepue and Solarin (2008); and
c) nature of further research in volatility modelling useful to investment analysts, academics and policy makers.

Section 9.2 of the chapter clarifies the concept of volatility as used in finance literature. Section 9.3 reviews linear regression and autoregressive models, while Section 9.4 discusses ARCH/GARCH and SV volatility models. Section 9.5 examines the rationale for ARCH/GARCH models. Section 9.6 discusses generalizations of ARCH/GARCH models. Section 9.7 applies selected GARCH models to NSM returns for the period 2000-2010 subdivided into pre-reforms (2000-2004), post reforms (2005-2010), post-reforms pre-crisis (2005-July 2007), and post-reforms post-crisis (August 2007-2010). Section 9.8 outlines related future research and Section 9.9 summarises and concludes of the chapter.

9.2 The concept of volatility

It is well known that errors made in modelling and forecasting the time series behaviour of financial markets typically vary over time due to uneven fluctuations in observed values of related financial quantities. For example, stock returns in the NSM (as seen in Chapters 5 and 6 of this thesis) appear to vary more wildly during the global financial crisis. This behaviour is known in statistics and finance literature as heteroskedasticity; it captures the fact that the size of market volatility clusters in periods of high and low volatility.

We alluded to this fact in the introduction to this chapter. It should be noted that heteroskedasticity is somewhat associated with complex nonlinear causative mechanisms underpinning market events, including effects of key economic indicators for example interest rates, consumer price index, oil prices, and shocks introduced by new policies and sometimes unforeseen events such as financial reforms and global financial crisis discussed in this research. Volatility models enable us to formalize this time-varying behaviour of variations in economic quantities such that we are able to simultaneously predict the variables and the average magnitude of the prediction errors involved.

In this chapter we concentrate attention on the use of GARCH models to study time-varying behaviour of NSM returns, but we also discuss alternative formulations in the form of ARCH and SV models. Firstly, we explain the technical meanings of volatility as distinct from standard deviation and risk which it connotes. In finance, "volatility refers to standard deviation σ or variance σ^2 calculated from sample observations as

$$\hat{\sigma}^2 = \frac{1}{n-1}\sum_{t=1}^{n}(r_t - \bar{r})^2 \qquad \text{Equation 9-1}$$

where $\bar{r}$ is the mean return. The sample standard deviation is a distribution free statistic associated with the second moment of the sample", Poon and Granger (2003 p. 480). Its distribution is in general estimated from the empirical distribution for all shapes of distributions possible, but is functionally known when the standard deviation is attached to standard distributions for example normal or t distributions. In the continuous time context, σ is a scale parameter that 'multiplies or reduces the size of the fluctuations generated by the standard Wiener process', Poon and Granger (2003 p. 480), Lefebvre (2006). Recall in this respect that a stochastic process $\{W(t), t \geq 0\}$ is called a Wiener or Brownian motion process if **i)** $W(0) = 0$, **ii)** $\{W(t)\}$ has stationary and independent increments, and **iii)** $W\{t\} \rightarrow N(0, \sigma^2 t)\ \forall t > 0$.

Depending therefore on the kind of stochastic process that generates the returns data and whether or not the parameters are time-varying, we encounter different shapes of return distributions. Hence, it is not meaningful to use σ as a measure of risk if it is not attached to a distribution that describes the price changes, Poon and Granger (2003), McDonald (1996). Indeed, σ is the correct risk measure for the normal distribution, but not all distributions, and we know that distributions in finance are rather non-normal in most cases, as seen in Chapters 5 and 6 of this thesis and explored intimately in McDonald (1996). Hence, to alleviate the effects of outliers in non-normal asymmetrical distributions other measures of dispersion are used for example mean absolute return, inter-quartile and other inter-quantile ranges.

Volatility however differs from risk and standard deviation even though all measure uncertainty; risk refers to small or negative returns while most measures of dispersion refer to negative as well as positive returns. For example, "the Sharpe ratio, $(r - f)/\hat{\sigma}$, defined as the ratio of excess return above the risk free rate of interest to the standard deviation, is commonly used as a measure of investment performance in portfolio analysis. By including all directions of return fluctuations (negative and positive) it incorrectly penalizes occasional high returns", Poon and Granger (2003, p. 480). This led to the idea of semi-variance which involves only squares of returns below the mean, but is not easy to operationalize in portfolio construction and therefore not widely used.

The above background enables us in this chapter to see volatility as a generalization of the concept of risk in more fluid situations in financial modelling for which key quantities exhibit time-varying behaviours with different types of distributions. The ARCH/GARCH models discussed in the chapter provide such generalizations. Indeed, volatility is, depending on context, calculated as the standard deviation (a squared-returns measure), absolute returns-based deviations, and continuous time analogues explained below. Poon and Granger (2003) discuss the performance trade-offs in using these different measures in forecasting volatility in financial markets. The emphasis of this chapter is on explanatory modelling of volatility behaviour in the NSM, but insights from the forecasting literature inform the choice of models anyway.

As explained in Poon and Granger (2003 p. 480), "for the continuous time analogue of equation (9.1) (a vestige of the Brownian motion formulation), we suppose that the instantaneous returns are generated by the continuous time martingale

$$dp_t = \sigma_t dW_{p,t} \qquad \text{Equation 9-2}$$

for which $dW_{p,t}$ is a standard Wiener process". From equation (9.2) the **conditional variance** for one-period returns $r_{t+1} = p_{t+1} - p_t$ is given by $\int_0^1 \sigma_{t+\tau}^2 d\tau$ in the period $(t, t+1]$. This quantity is known as the integrated volatility over the period and is central to the pricing of derivatives using stochastic volatility models. The integration in equation (9.2) is relevant in such analysis since prices or returns and other financial quantities of interest in volatility analyses are described by a continuous-time continuous-state space stochastic process. The definition of one-period returns here is based on asset prices but is generic for other concepts of returns for example the market index returns in this thesis for which prices are replaced by log indexes. Technically, p_t is observable at time t but the volatility σ_t is a latent variable which scales the underlying Wiener process. The question of interest therefore is how we measure this volatility or more precisely what regularity condition on the character of the stochastic generating process enables us to do so. For this, let there be m continuously compounded returns in one unit time interval such that $r_{m,t} \equiv p_t - r_{t-1/m}$. This is simply a discrete sampling of returns to approximate the continuous price with the last observed return in the interval $(t,\ t+1]$. From the theory of quadratic variation in stochastic calculus, Karatzas and Shreve (1988) quoted in Poon and Granger (2003, p. 481), and given serially uncorrelated sampled returns and continuous sample path for σ_t, we have that

$$\int_0^1 \sigma_{t+\tau}^2 d\tau \xrightarrow{p} \sum_{j=1}^{m} r_{m,t+j/m}^2 \quad \text{as } m \to \infty. \qquad \text{Equation 9-3}$$

This result asserts that the time t volatility can be estimated from the sampled path of the return process if the process is frequently sampled. This yields the realized volatility of the return process as the sum of intraday squared returns at very short intervals such as 5–15 minutes. “Such volatility estimators accurately estimate the latent process that defines return volatility”, Poon and Granger (2003, p. 481). It is also known that measuring returns at less than 5 minutes produces spurious serious correlations due to micro-dynamics of the market.

From a forecasting point of view, Poon and Granger (2003) state that using squared returns for non-normal returns distributions can produce poor forecasts (or wider forecast errors). These notes are important for us in this chapter because:
a) they show why volatility analysis is best carried out with daily returns which is the highest returns frequency in the NSM returns, observed at discrete time points (daily, weekly, monthly and yearly) within the study period 2000-2010, and
b) they explain why different forms of volatility measures feature in various classes of volatility models for example absolute errors, squared errors and log-errors, as appropriate. Finally, though this chapter does not use continuous time volatility modelling in great detail, except in brief discussion of stochastic volatility models, the above ideas enable us to discuss wider issues of volatility analysis linked to systematic characterisation of the NSM and other emerging African markets, subsequently in the chapter.

The following section on linear regression and autoregressive models which are commonplace in mainstream time series analysis enables us to explicate the key concepts encountered in volatility modelling such as conditional variance or standard deviation (already used in the above notes), conditional mean, error and innovation process, various guises of stationarity, and to justify why extensions to ARCH/ARCH modelling is necessary in the context of heteroskedasticity.

9.3 Review of linear regression and autoregressive models

A linear regression model denotes a proportionality relationship between a dependent variable, say, returns and a predictor variable x of the form

$$r = \alpha + \beta x + \varepsilon \qquad \text{Equation 9-4}$$

In this representation the expected return is β times the expectation of x plus a generalized constant which subsumes the effects of other influences not measured by x. This linear relationship is not exact, hence the error term ε typically assumed to have a zero mean and a constant standard deviation σ. Since the error term has a zero mean we easily express the variance of returns as $\sigma^2 = E(\varepsilon^2)$. The notion that this variance is constant and independent of the size of x is called homoskedasticity as opposed to heteroskedasticity when it varies with the size of x. While mathematically convenient, homoskedasticity is not reasonable when the range of the variable is large or the variable is likely to vary in behaviour over time, as explained in the introduction to this chapter. For instance, NSM returns over such a long period 2000-2010 in this study are more likely to vary disproportionately in response to any moderating variables which fluctuate with time rather unevenly for example interest rates, oil prices, market and asset prices and risks, price/earnings ratios of stocks, and due to policy shocks from, say, bank reforms and global financial crisis. We attach the time element to these variables so that instead of the cross-sectional representation in equation (9.4) we consider the returns time series as a stochastic process $\{r_t\}$ for which each t-value is an observation of a random variable.

Formally speaking, we see the stochastic process as a sequence of random variables characterized by a joint probability distribution for every finite set of time points. Let f_t be the corresponding marginal distributions at each time point t. The stochastic process $\{r_t\}$ is intuitively a very large (infinite) number of paths linking all possible positions of the values as time progresses. The process is called weakly stationary if all its moments up to order two are constant, that is mean and variance are constants $\mu_t = \mu$ and $\sigma_t^2 = \sigma^2$. The process is called strictly stationary if its finite distributions are time independent. Note that a strictly stationary process may have finite distributions with infinite moments, so it may not be weakly stationary. The mean and variance terms just stated are unconditional moments of the process. In finance and economics as is the case in the financial market analysis in this chapter, we aim to use past and present information to predict future values of financial quantities of interest, particularly returns and their volatilities. Hence, we consider the conditional distribution of returns now and in the immediate past $f(r_t \mid \Omega_{t-1})$ and corresponding conditional mean and variance $(\mu_t \mid \Omega_{t-1})$ and $(\sigma_t^2 \mid \Omega_{t-1})$ where Ω_{t-1} is the market information up to time t-1.

The gist about heteroskedasticity is that a process can be weakly stationary in terms of the unconditional mean and variance but have time-varying conditional variance. Importantly, if the conditional mean is constant, then the unconditional variance is the unconditional expectation of the conditional variance. If the conditional mean is not constant, this fact does not hold as a result of properties of conditional and iterated expectations. Since the variance in question is the expectation of squared error process as mentioned above, ARCH/GARCH modelling of returns is focused on the error process. We particularly assume that the errors constitute an innovation process, that is, the conditional mean of the errors is zero. This is formalized in the expression $\varepsilon = \sigma_t z_t$ where σ_t is the conditional standard deviation and $\{ z_t \}$ are i.i.d. N(0,1) distributed random variables (a white noise process). This assumption guarantees that the unconditional variance of the error process is the unconditional mean of the variance of the return process, which is not the case under other specifications of the error process. In financial models conditioning is usually stated as autoregressive model of future returns on present and past values of returns as follows:

$$r_{t+1} = \beta_0 + \sum_{i=1}^{n} \beta_i r_i + \varepsilon_{t+1} \qquad \text{Equation 9-5}$$

where the error term is conditional on the information in past and present returns up to time t. The simplest autoregressive model for NSM log indexes (which informs our treatment of market efficiency in Chapter 6 of this thesis) is given by $\ln I_{t+1} = \mu + \ln I_t + \varepsilon_t$ so that returns expressed as difference in log indexes at successive periods performs a random walk with drift μ defined as $r_t = \Delta \ln I_t = \mu + \varepsilon_t$.

We note that two different types of heteroskedasticity have been introduced above: first, regression errors vary with the size of the predictor variables; second, error terms are conditionally heteroskedastic because they vary with time and not necessarily the size of the predictor variables. More general ARCH models have error heteroskedasticity associated with both predictor variables and time. In sum, different ARCH/GARCH models depend on different specifications of heteroskedasticity in the error term. To take a simple example, consider the simple random walk model of returns $r_t = \mu + \varepsilon_t$ versus a model $r_t = \mu + f_{t-1} + \varepsilon_t$ which assumes that returns are predictable through a regression on a predictor variable f. This model will be more accurate by using additional information so the errors will be smaller than those in the random walk model, thus the heteroskedastic behaviour will vary.

The significance of these suppositions is this: if the errors in the random walk model are an innovation process, then their variances coincide with the unconditional variance of returns around the mean return. This way, ARCH specification effectively describes returns behaviour. But if we are able to predict returns using the factor model, then the ARCH specification describes the behaviour of errors and not returns, since the unconditional variance of errors fails to coincide with the unconditional variance of returns. This is somewhat an argument in semantics, for what is material in ARCH/GARCH modelling is that the true data generating process for returns is identified or, if not exactly identified, robust enough to produce meaningful accurate forecasts of returns volatility, Poon and Granger (2003).

In line with the preceding statement, it is well known that ARCH/GARCH models are suitable for a variety of empirical data typically encountered in financial econometrics because these data exhibit conditionally heteroskedastic errors, Poon and Granger (2003), Engle (2001). In this thesis, we have noted in Chapters 5 and 6 some evidence of non-normal, chaotic behaviour in NSM returns leading to weak-form inefficiency of the stock market. We have also noted evidence of time-varying volatilities in returns across sub-periods of the study corresponding to financial reforms and the global financial crisis. Whilst the efficiency tests reject the random walk hypothesis and indicate nonlinearities in returns over time, the ARCH/GARCH analyses in this chapter complete the arc of empirical modelling of NSM key characteristics in this research for example efficiency, bubbles, anomalies and volatility, at overall market level. In a sense, the general suitability of ARCH/GARCH models discussed here enables us to triangulate previous results on these other market characteristics from the volatility modelling results.

9.4 ARCH/GARCH and stochastic volatility (SV) models

In this section we further explain the key ideas in ARCH/GARCH modelling. Basically, ARCH/GARCH models extend the linear/autoregressive models of returns (or any other financial quantities of interest) by representing returns as a sum of a (time dependent) mean and a time-varying error term composed (in the simplest case) of a scaling of a white noise process with a variance function $h_t = \sigma_t^2$. The use of h simplifies our notations henceforth. The standard deviation, variance, and absolute deviation of empirically calibrated power functions of h, may be used in various ARCH/GARCH models. We write the simple ARCH model introduced in the foregoing notes as:

$$r_t = \mu_t + \sqrt{h_t} z_t \quad \text{Equation 9-6}$$

Interest in ARCH/GARCH modelling of empirical finance data is on estimating and forecasting the mean and variance of the returns conditional on past information. While many extensions of the ARCH/GARCH models are formulated to take account of different aspects of the data behaviour for example asymmetric effects of good and bad news, degrees of volatility clustering, and mean reversion, simpler models have proved quite successful in predicting conditional variances, Engle (2001), Poon and Granger (2003). This fact motivates our use of ARCH(1,l), GARCH (1,1) and related low-order models in this chapter, especially when our principal objective is to map the overall character of returns volatility in the NSM, as opposed to detailed forecasting and evaluation of future volatility values; see Poon and Ganger (2003) for detailed treatment of volatility forecasting and evaluation in financial markets.

An immediate extension of equation (9.6) would be to drop the assumption of white-noise behaviour in the error term $\varepsilon_t = \sqrt{h_t}\, z_t$ where z_t is the white-noise component. If strict white-noise assumption holds ($\varepsilon_t = z_t$ are zero-mean, independent with same variance), the error variance is easily estimated as the empirical variance $h = \sum_{i=1}^{n} \varepsilon_i^2 / n$ using the largest available sample information, hence the use of daily data in our analyses, as explained earlier. Moreover, in the heteroskedastic formulation in equation (9.6), a strategy for dealing with time dependency uses a short rolling window estimation process to obtain rolling standard deviation and variance, Poon and Grange (2003). A vestige of the Kalman-filter approach to statistical modelling, this in effect uses a fixed number of the most recent observations on the supposition that the variance changes slowly over time and is approximately constant in a short rolling window. The drawback of this approach is that it gives equal weights to all data points in the window, whilst it could be argued that more frequent observations are more relevant and should carry more weight in specifying the dynamics of returns. This is where ARCH models come into use in volatility modelling.

Hence, in the ARCH model originally proposed by Engle (1982), the weights are parameters to be estimated from the data according to some optimality criterion for example maximum likelihood and computationally through suitable model selection criteria such as Akaike Information Criterion (AIC). In this formulation the variance is modelled as a weighted moving average of past error terms as follows:

$$h_t = \omega + \sum_{i=1}^{p} \beta_i \varepsilon_{t-i}^2 + \varepsilon_t \qquad \text{Equation 9-7}$$

with error terms still retaining the scaled white noise structure in equation (9.6). To ensure that variance is nonnegative, the variance parameters omega and betas must all be nonnegative. If the betas sum to less than 1, the ARCH process is weakly stationary guaranteeing the existence of a constant unconditional variance given by:

$$h = \sigma^2 = \frac{\omega}{1 - \sum_{i=1}^{p} \beta_i} \qquad \text{Equation 9-8}$$

It is noteworthy that the ARCH model is innately a forecasting model in so far as the model yields forecasts of error variance at time t on the basis of market information up to time t-1 and the expected squared error is constant, that is, without uncertainty as required of forecasting models. However, the observed squared errors may differ widely from this forecast value, hence emphasis in volatility modelling on optimal choice of models using relevant performance criteria such as Akaike Information Criterion (AIC), Schwartz Crierion (SC) and Hannan-Quinn Criterion (HQC) in our EViews volatility analyses in this chapter.

The GARCH model introduced by Bollerslev (1986) generalizes the above features of the simple ARCH model in some interesting ways. First, it is imbued with declining weights that never attain zero values. This way it is in its most general form non-Markovian as all previous errors affect the volatility forecasts. It is known also that this model is parsimonious with easy-to-estimate parameters and is 'surprisingly successful in predicting conditional variances', Engle (2001, p. 159), Poon and Granger (2003). This again justifies our focus on GARCH models in this chapter. Moreover, the slow decay of the model parameters which drags so many previous errors into the observed volatility results makes this class of models particularly agile in capturing volatility persistence due to long-lasting effects of financial news, events, shocks, policies, financial crises, and volatility correlations among cognate financial assets or dominating prices in the economy for example oil prices in Nigeria, Poon and Granger (2003 p. 481-484).

The most commonly used GARCH model states that the best next-period variance predictor is a weighted average of the long-run variance, the current period variance, and new information in the current period, a kind of adaptive learning behaviour akin to Bayesian updating, Cuthbertson and Nitzsche (2005, p. 423-488), Engle (2001, p. 160). This model is labelled GARCH(1,1) to denote the fact that its volatility component incorporates 1 return variance term (or autoregressive lag) and 1 volatility term (or ARCH term) reads as follows:

$r_t = \mu_t + \sqrt{h_t}\varepsilon_t$; where $h_{t+1} = \omega + \beta_1(r_t - \mu_t)^2 + \beta_2 h_t = \omega + \beta_1 h_t \varepsilon_t^2 + \beta_2 h_t$ Equation 9-9

In this specification, the variance of the error term ε_t is 1. If we make recursive substitutions in equation (9.9) we obtain an infinite weighted moving average with weights which are different from standard exponentially weighted moving average (EWMA) models of the kinds discussed in Chapter 5 of this thesis. The periodic updating of the parameter estimates for the constant and betas in this model simply requires knowledge of previous volatility forecast h and the residual. It is known that the appropriate positive weights from the model are given as $(1-\beta_1-\beta_2, \beta_2, \beta_1)$ and the long-run average variance is $\sqrt{w/(1-\beta_1-\beta_2)}$ subject to the restraints of positivity for all the parameters and $\beta_1 + \beta_2 < 1$. Structurally, the GARCH (1,1) process is weakly stationary given the last mentioned constraint and strictly stationary if $E[\log(\beta_1 z^2 + \beta_2) < 0$. The GARCH (1,1) model with the equality condition $\beta_1 + \beta_2 = 1$ is therefore strictly stationary and is called an integrated GARCH or IGARCH model. It is imbued with infinite variance.

Practically, though the model is seemingly set up to predict one-step-ahead volatilities, recursive substitution of previous forecasts in succeeding forecasts enables the model to produce long-horizon forecasts. This is again the reason why GARCH (1, 1) model and related low-order GARCH models discussed in this chapter are versatile workhorses in volatility modelling. Moreover, as mentioned above, the long-horizon volatility forecast for the weakly stationary GARCH (1, 1) process gives the same value stated above based on the sum to infinity of the geometric beta-parameter terms in the infinite recursive substitutions; this forecast value is just the unconditional variance of the model. In a sense, the GARCH (1, 1) model mimics an ARMA (1, 1) model in standard time series analysis.

To shed more light on maximum likelihood estimation of the model parameters, the GARCH (1, 1) model is computationally and recursively estimated from a single set of returns using, say, normal likelihood approach, by substituting h_t for variance in the likelihood function and maximizing with respect to the parameters. This is implemented in standard statistical computing software for example MATLAB, SAS and EViews; we use EViews in this thesis. A simple diagnostic for model fitness is to plot the resulting error terms which are supposed to have a constant mean and variance if the model is correctly specified. Statistical tests in aid of such diagnosis involve detecting autocorrelations in the squares using, say, the Ljung-Box test with 10-15 lagged autocorrelations. In this chapter we use this test with 10 lags which is sufficient for this purpose, Islam and Watanapalachaikul (2005). We now take a brief look at stochastic volatility models.

9.4.1 Stochastic volatility (SV) models

In this modelling framework, volatility is subject to marketplace or wider economy-based innovations that may or may not be directly related to the forces that drive returns. The framework is more directly related to options-based volatility forecasting in the guise of the Black-Scholes option-pricing model. For this thesis and in the interest of broad recommendations for research on stock market characterisation of the NSM discussed here, we motivate intuitively the links between SV and ARCH/GARCH volatility modelling. Ramifications of SV modelling are referred to relevant references given in this section.

"The Black-Scholes model for pricing European equity options originally proposed by Fischer Black and Myron Scholes in (1973) assumes the following stock price dynamics:

$$dS = \mu S dt + \sigma S dz \qquad \text{Equation 9-10}$$

With corresponding growth rate (returns) on stock given in absolute and logarithm forms as:

$$\frac{dS}{S} = \mu dt + \sigma dz \qquad \text{Equation 9-11}$$

$$d\ln S = \left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma dz \qquad \text{Equation 9-12}$$

Equation (9.12) is a consequence of Ito's lemma in stochastic calculus and as known in mathematical finance implies that stock prices have a lognormal distribution", Poon and Granger (2003 p. 485).

The import of this remark in this thesis is that an interesting pathway for research on stock market dynamics in Nigeria and emerging African markets is the use of a multidisciplinary approach involving applied statistical modelling, stochastic processes, stochastic calculus, mathematical finance tools, empirical finance and applied econometric tools, statistical physics (econophysics) tools, complexity theory and simulation, and experimental economics tools.

Intuitively, a look at equations (9.11) and (9.12) in comparison with the basic ARCH model shows how close the formulations are; the difference is that the dependence of the constant term μ_t in the SV model on time is specified as a simple product of the change in time. As a local approximation, therefore, within a small neighbourhood of time, the SV model would appear to accommodate the 'instincts' of ARCH/GARCH models. Moreover, the model is appropriate for modelling continuous time variation of underpinning financial variables for example exchange rates, asset prices and interest rates. We also remark that using lognormal distribution for returns and other variables as the data generating distributions in ARCH/GARCH models conflates ARCH/GARCH volatility modelling with SV volatility modelling.

With the above motivations in place, we display the character of SV return models as follows. A discrete SV model which is relevant for returns analysis is defined as:

$$r_t = \mu_t + \sqrt{h_t}\varepsilon_t \text{ where } \varepsilon_t \text{ is i.i.d.} \qquad \text{Equation 9-13}$$

and the volatility component is specified as:

$$h_{t+1} = \beta h_t + \eta_t,\ |\beta| < 1 \qquad \text{Equation 9-14}$$

where η_t is an innovation process. Not surprisingly because of the aforementioned close affinity between ARCH/GARCH and SV models, this simple SV model with AR (1)-type volatility specification is satisfied by the Exponential GARCH (EGARCH) model discussed below and ensures positive conditional variance, Islam and Watanapalachaikul (2005, p. 129).

The picture is not that simple since there are several types of SV models including the discrete-time SV, continuous-time SV as in equations (9.10) to (9.12), and jump diffusion SV models, not discussed here. There are advantages in using SV models which include: properties that are easier to manipulate compared to ARCH/GARCH models; the fact that the models may better track the fat tail property associated with skewed and leptokurtic returns distributions; their correspondence with ARCH/GARCH models in certain cases as explained below; and their ability to capture asymmetry in the returns process, Islam and Watanapalachaikul (2005), Poon and Granger (2003).

As we might expect, SV models are not superior to ARCH/GARCH models in all respects and situations especially in modelling asset prices and returns; in any case some of their properties can still be achieved by some ARCH/GARCH models for example volatility persistence in SV models is captured through a random walk specification in the IGARCH model. From a theoretical perspective, SV models have no closed form solution except in the simple Black-Scholes framework, hence they cannot be estimated directly by maximum likelihood, and the quasi-maximum likelihood (QMLE) approach of Harvey and Shephard (1994) quoted in Poon and Granger (2003) is inefficient with non-Gaussian volatility proxies. Alternative estimation methods are generalized method of moments (GMM) through simulations, numerical integration and Monte Carlo integration.

For a rich survey of SV models see Ghysels et al. (1996) and for interesting applications of the models in different theoretical and modelling contexts including multivariate SVs, see Yu et al (2006), Chan et al. (2006), Asai and McAleer (2007), Asai et al (2006), Kim et al (1998), Chib et al (2002), Danielsson (1998), Chib et al (2006), and Yu and Meyer (2006).

9.5 The Rationale for ARCH/GARCH models

We have seen that ARCH/GARCH models are very successful in modelling volatilities since many empirical finance phenomena exhibit volatility clustering, a tendency for small and large changes in, say, stock indexes and returns to be followed by small and large changes over time. As noted, ARCH/GARCH models account for the time evolution of average size of squared errors which define uncertainties in financial time series (of returns). Notwithstanding this empirical success of these models, there is no agreement regarding the economic reasons for volatility clustering, with the consequence that some of the models perform better or poorly in different periods and contexts. Heuristically, therefore, optimal choice of ARCH/GARCH models has to reckon with the background knowledge of the financial economic context which underpins volatility clustering, symmetric or asymmetric effects of system shocks (internal and external) and the empirical fit of the models, in a contest among different model types which is adjudicated by the statistical characteristics of the observed data.

With respect to NSM returns, we attempted in the foregoing sections to rationalize volatility clustering in terms of policy shocks from the 2004 bank restructuring in Nigeria, the global financial crisis, uneven fluctuations in oil prices which drives the Nigerian petro-dollar economy, and frictions associated with information transmission and flow in the Nigerian financial system. At least from the empirical perspective, work in Chapters 5 and 6 of this thesis reveal asymmetries, non-normality and leptokurtosis in returns distributions across the different study periods – entire period, pre-reform, reforms, and crisis periods – to the extent that ARCH/GARCH modelling in this chapter triangulates previous results on weak-form inefficiency in the NSM.

In experimental finance and economics it is fairly easy to simulate ARCH behaviour using appropriate assumptions about the behaviours of market agents (households, firms and governments). The realism of such assumptions leans somewhat on fundamental analysis of market conditions, known histories of reactions of asset prices to plausible shocks in the system, likelihood of herd behaviour on the part of the agents, use of overall market information and personal information by the agents, strength of contagion in the market moves played out by the agents, force of emotional reactions of agents to market making news, Knight (2011), rate of diffusion of information through the financial market (informational efficiency), degree of asymmetry in the conditional density functions underpinning returns behaviour, and comparative performance of classical versus behavioural finance models of asset prices, Cuthbertson and Nitzsche (2005), Forbes (2009), Poon and Granger (2003), Engle (2001, p. 166), Topol (1991), McDonald (1996), Bond (1996) and Fritsche (1996).

At the moment in Nigeria there is virtually no work in the literature which addresses these stock market characterisation issues. This thesis is part of a long-term research on systematic characterisation of the NSM and other emerging African markets which we will discuss subsequently in the chapter. As mentioned in the introduction to this chapter, the contribution of volatility modelling here is not only to explicate volatility dynamics in NSM for policy and stock market development purposes, but also to assess the suitability of selected volatility models for on-going volatility modelling required in this systematic characterisation. Hence, we could analyse for example asset price volatility modelling in key market sectors and case companies, interest rate, exchange rate, oil price, stock market volume and market capitalization volatilities. For this reason, we explore the rationale for ARCH/GARCH models a bit more here.

A number of stylized facts about financial market volatility, some of which have been discussed in the foregoing notes, inform the use of ARCH/GARCH models. "These include:

- fat tail distributions of asset turns; volatility clustering;
- asymmetry between effects of bad and good news, whereby bad news provoke higher volatility than good news or otherwise, say;
- comovements of volatilities across market sectors and asset classes as a result of strong correlations among volatilities;
- (non) i.i.d. and/or white-noise behaviour of asset prices and returns;
- persistence of volatility in period data on asset prices for example daily and intraday returns;
- mean reversion in volatilities, whereby errors hug the average values of asset prices, so that the volatility models are not explosive (that is, have near infinite variance), but are stable and weakly stationary; and
- preservation or not of volatility structure through inter-temporal aggregation, that is, whether the pattern of hourly, daily or monthly volatilities remains the same", Poon and Granger (2003, p. 481-483).

The different ARCH/GARCH models discussed in this chapter, though only some of them are finally selected for the empirical analyses of NSM returns volatility, capture volatility persistence, clustering and asymmetry to different degrees. An alternative approach to volatility modelling apart from empirical data-driven approach is theory-based modelling. In this approach, one can construct supply and demand models for financial assets, with either of these components imbued with some realistic assumptions about their approximate constancy or noisiness, any external instruments that introduce nonlinearities in the models for asset returns, and likely families of distributions which fit the data. In this chapter we adopt primarily the empirical approach and allow the returns data to tell us the story of what is really happening 'beneath the arches'. Our results will inform more theoretical volatility modelling anticipated in the systematic characterisation of the NSM described above.

Also, apart from the ARCH/GARCH models, there are simpler approaches to measuring volatility which, under certain conditions related to the empirical character of returns, can produce good volatility forecasts for within- and out-of-sample volatility forecasting, Poon and Granger (2003). These methods include the simple random walk model, historical average, moving average, exponential smoothing, exponentially weighted moving average, simple regression (AR), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) methods.

We feel that a systematic characterisation of the NSM using the pooled skills of academics and research students in various Nigerian universities should be able to provide a taxonomy of the efficacies of these approaches for modelling volatilities in different market sectors; see Knight (2011) for a description of this approach to financial markets research at the University College London. This chapter merely anticipates this line of future work and does not discuss these approaches further. We offer more insights on the rationale for different ARCH/GARCH models in the following section, on our way to selecting the preferred models used in this chapter.

9.6 Generalizations of the ARCH/GARCH models

The ARCH/GARCH modelling frameworks have been extended and generalized in many different ways by several authors. We discuss some of these extensions and generalizations in this section, or at best provide references detailing the developments. There are three main extensions and generalizations of wide interest in finance and economics:

a. integration of first, second and higher moments;
b. generalization to high-frequency data; and
c. multivariate extensions, Engle (2001), Focardi and Fabozzi (2005).

With respect to integration of moments, we note that in the ARCH/GARCH models returns are assumed to be normally distributed and forecasts of first and second moments independent. We can relax these assumptions in a number of ways. The conditional distribution of the error can be non-normal as with the lognormal distribution underpinning the stochastic volatility models. In empirical approach to volatility modelling discussed above, it is safer to allow the data to determine the type of distribution that governs returns. Also, the first and second moments can be integrated in a model that no longer keeps them independent of one another.

An interesting extension of ARCH/GARCH models deals with asymmetries between good and bad news for example the fact that falls in asset prices produce higher volatility than comparable increases. Structurally, this means that the direction of the errors affects volatility. Some asymmetric GARCH models include the Exponential GARCH (EGARCH) model of Nelson (1991), the Threshold ARCH (TARCH) model of Rabemananjara and Zakoian (1993) and the Glosten et al. (1993) GJR-GARCH model. To explicate the asymmetric GARCH mechanism, consider the GJR-GARCH model thus:

$$h_{t+1} = \omega + \beta_1 h_t \varepsilon_t^2 + \gamma(I_{\{\varepsilon_t<0\}}\varepsilon_t^2) + \beta_2 h_t \qquad \text{Equation 9-15}$$

The indicator term in (9.15) is zero when the error is positive and 1 when the error is negative, hence leveraging the effect of declines in returns compared to increases, which is implied by asymmetry. The parameters of the model are assumed to be positive and the relationship between the parameters that guarantees reliability of the estimates is $\beta_1 + \beta_2 + \gamma/2 < 1$.

Another extension of GARCH models deals with the stylized fact that residuals of ARCH/GARCH models of empirical finance data display excess kurtosis, as found in Chapters 5 and 6 of this thesis, by using other distributions for example Bollerslev (1986) uses the t-distribution. Indeed, the t-distribution underpins the EViews error distributions in our empirical results.

We now look at the integration of first and second moments in the GARCH-M model. The logic of this integration is that it is necessary not to treat mean and variances as independent, since in financial risk management there is a relationship between expected return and risk (variance). Indeed, predictability of returns as a function of risk is a natural consequence of the rational expectations hypothesis and does not violate market efficiency. Hence, in order to link changes in volatility with changes in returns, Engle et. al (1987) introduced the GARCH-M model thus:

$$r_{t+1} = \mu_t + \sigma_t z_t; \quad \mu_t = \mu_0 + \mu_1 \sigma_t^2 \qquad \text{Equation 9-16}$$

Here σ_t^2 follows a GARCH process and the z terms are i.i.d. Normal variables. The GARCH-M label is because the GARCH component is associated with the mean return process; instead of expressing the mean as a linear function of variance, it can be linear in standard deviation.

We now comment on extensions to high-frequency data; this is important because of the advent of electronic trading which releases huge masses of tick-by-tick data from the financial markets. This has led to an emerging field of high-frequency or high-density finance with associated techniques in algorithmic or computational trading, Knight (2011). The key issues to consider in this scenario include: discovery of arbitrage opportunities using intraday risk analysis; improvement of forecast precisions through such granular data; similar precision arguments in diffusive models of volatility for which hourly, daily or weekly data are preferred to longer epochs for example monthly data; relaxing the regular spacing of the data points to make use of randomly occurring 'ultra-high-frequency data' (natural statistical models here involve point stochastic processes), Engle (2000); and the *temporal aggregation problem,* mentioned earlier, which looks at persistence or otherwise of volatility structure across horizons of data used for example daily, weekly and monthly. The latter enables us to gauge whether some phenomena for example volatility exist at some horizons and disappear at other horizons. For example, in Chapter 6 of this thesis we noted that the NSM is weakly inefficient for daily data in almost all periods of the study, but less so for monthly post-reforms data.

Technically, a GARCH (p,q) process (discussed below) may not be preserved as a volatility model for data at different levels of time aggregation because the underpinning assumption that GARCH error series $\{\varepsilon_t = \sigma_t z_t\}$ be a martingale difference sequence with zero conditional mean does not hold at longer time horizons. This again is the reason why we can at best model volatilities with daily or weekly data as in this chapter. Increasingly, this problem is overcome through the so-called weak GARCH processes of Drost and Nijman (1993) who show that weak GARCH (p,q) models are closed under temporal aggregation. What this means is that we draw respite in using these models since we may not worry too much about what time horizon to use in volatility modelling, but the model typically masks volatility fluctuations at very large horizons.

Meddahi and Renault (2004) propose a class of autoregressive stochastic volatility (SR-SARV) models that are closed under temporal aggregation and thereby overcome the limitations of weak GARCH models. Also Andersen and Bollerslev (1998) propose realized volatility as a very precise measure of instantaneous volatility based on high-frequency squared terms. These reviews are still concerned with regularly spaced observations. Particular interest has arisen with regards to random point high-frequency data generated by electronic trading which naturally clusters orders into periods of intense trading activity and relative quiet. As mentioned earlier, techniques for dealing with high-frequency data involve the theory of point stochastic processes for example through the autoregressive conditional duration (ACD) model of Engle and Russell (1998) and the ACD-GARCH model of Ghysel and Jasiak (1997). Though we do not pursue these perspectives further in this thesis, we are prepared to exploit such models in the future in NSM characterisation, since the Nigerian Stock Exchange has been digitalized, a development that will spur advancement towards electronic trading in the NSM.

We do not dwell too much on multivariate extensions of GARCH (M-GARCH) models; a lucid introduction to this class of models is offered in Engle et.al (2007, p. 9-10). We note that the ideas are relevant to portfolio management and theory and aggregate the univariate GARCH constructs into vectors and correlation matrices of the kinds typically encountered in n-asset portfolio optimization. Again, we will keep such models in view as we progress the said research on stock market characterisation in Nigeria and other emerging African markets.

9.6.1 Illuminating notes on GARCH (p,q) models

In order to foreground interpretation of the empirical results in section 9.7 below, we recall the model forms for the class of GARCH (p, q) models used in this chapter. Our model parameterizations and empirical modelling lean heavily on Islam and Watanapalachaikul (2005, p. 129-146). There may be overlaps between this sub-section and earlier notes but this is good for emphasis.

GARCH (p, q) model

This model is defined as

$$r_t = \mu + \sqrt{h_t}\varepsilon_t \qquad \text{Equation 9-17}$$

$$\begin{aligned} h_t = \sigma^2 &= \omega + \sum_{i=1}^{q}\alpha_i(r_{t-i} - \mu)^2 + \sum_{i=1}^{p}\beta_i h_{t-i} \\ &\equiv \omega + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i h_{t-i} \end{aligned} \qquad \text{Equation 9-18}$$

As seen before, the GARCH (1,1) process produces multi-period volatility forecasts and when $\alpha_1 + \beta_1 < 1$ the unconditional variance of ε_{t+1} is $\omega/(1-\alpha_1-\beta_1)$. If we rewrite the GARCH (1,1) process as

$$h_t = \omega + \alpha\varepsilon_{t-i}^2 + \beta h_{t-1}$$
$$\equiv \omega + \alpha(\varepsilon_{t-1}^2 - h_{t-1}) + (\alpha+\beta)h_{t-1} \qquad \text{Equation 9-19}$$

we see from equation (9.20) below that the sum coefficient measures the rate at which the volatility effect reduces over time

$$E_t(h_{t+j}) = (\alpha+\beta)^j\left[\frac{h_t - \omega}{1-\alpha-\beta}\right] + \left[\frac{h_t - \omega}{1-\alpha-\beta}\right] \qquad \text{Equation 9-20}$$

EGARCH (1, 1) model

As motivated in earlier notes on model extensions, the dependence of the volatility process on both the sign and size of lagged residuals enables the EGARCH (1,1) model to better capture thick tails and volatility clustering in returns. This model is specified thus:

$$\ln h_t = \omega + \beta \ln h_{t-1} + \gamma\left(\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \left(\frac{2}{\pi}\right)^{\frac{1}{2}}\right] + \delta\left[\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right]\right) \qquad \text{Equation 9-21}$$

The model yields a positive conditional variance h_t for any choice of ω, β, γ so that there are no restrictions on these parameters, but the restriction $-1 < \beta < 1$ applies to the model. Importantly, the model captures asymmetries in ε_t since it contains both absolute and ordinary errors normalized by the standard deviation, and for negative δ it manifests higher volatility for large negative errors. Hence, the EGARCH model is suitable for capturing asymmetric shocks in NSM returns from, say, bank restructuring (financial reforms), global financial crisis, and oil price volatilities.

GARCH-M (1, 1) model

This model incorporates an autoregressive conditional heteroskedasticity (ARCH) component specified in equations (9.6) and (9.7) above. As we noted earlier, the model links or integrates returns with volatility and is specified with ARCH-M return and GARCH-M volatility components thus:

$$h_t = \omega + \alpha\left(\varepsilon_{t-1}^2\right) + \beta(h_{t-1}) \equiv \omega + \alpha\left(\varepsilon_{t-1}^2 - h_{t-1}\right) + (\alpha+\beta)h_{t-1} \qquad \text{Equation 9-22}$$

and ARCH-M

$$r_t = \psi h_t + \varepsilon_t \qquad \text{Equation 9-23}$$

where $\varepsilon_t = v_t\sqrt{h_t}$, $v_t \sim N(0,1)$ and $h_t = \omega + \lambda + \alpha\varepsilon_{t-1}^2$.

The returns can be expressed as

$$r_t = \psi(\omega + \lambda + \alpha\varepsilon_{t-1}^2) + \varepsilon_t \qquad \text{Equation 9-24}$$

The estimation of this model class requires correct specification of the entire model and is therefore numerically unstable. In this chapter our focus is not on technical model diagnostics, so we estimate this model from NSM returns in order to compare its results with those of other GARCH models, as a way of triangulating our search for plausible models for NSM returns volatility.

GJR-GARCH model

Again, this model links mean returns and volatilities and is an alternative to the GARCH-M model. It serves similar purpose in NSM returns modelling as we have stated in the case of the GARCH-M model. The GJR-GARCH model is specified as follows:

$$r_t = \mu + x_t^T b_i + \varepsilon_t \qquad \text{Equation 9-25}$$

and

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i (\gamma s_{t-1}) \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sqrt{h_{t-i}} \qquad \text{Equation 9-26}$$

The path to conditional volatility effects in this model is through squared residuals and as noted earlier the model is suitable for capturing asymmetries based on the parameter γ, which, when positive, accentuates the effects of negative residuals even more compared with positive residuals.

Importantly, the returns component in equation (9.25) justifies the use of external predictor and dummy variables in GARCH models which is the approach we take in this chapter. That is, we use dummies for days, weeks, months and years as appropriate to try to gauge the effects of these variables on NSM returns, which, though not directly associated with the volatility component, will enable us identify which of the variables have significant effects on returns, and may therefore account for the observed volatilities. As argued earlier in the chapter, this approach triangulates some of the results obtained in Chapters 7 and 8 of the thesis on bubbles and anomalies, which are linked to volatilities anyway.

PGARCH model

The Power GARCH model of Ding et al. (1993) is specified as follows:

$$h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{2} \alpha\left(\left|\varepsilon_{t-i}\right| + \omega\varepsilon_{t-i}\right)^2 \qquad \text{Equation 9-27}$$

A consequence of volatility persistence is that the sample autocorrelation function for absolute returns and squared error terms are significantly positive for very long lags. Also, the pattern of the sample autocorrelation varies for different stock returns and differently from theoretical autocorrelations given by the GARCH (p,q) or EGARCH (p,q) models. Consequently, Ding and Granger (1996) propose a two-speed PGARCH model in stated in equation (9.28) below

$$h_t = \frac{\omega}{(1-\beta_1)(1-\beta_2)} + \sum_{i=1}^{p} \alpha_1 \beta_1^{i-1} \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \alpha_2 \beta_2^{j-1} \varepsilon_{t-j}^2 \qquad \text{Equation 9-28}$$

The model uses two variance components with exponentially decreasing autocorrelation patterns to model the long-term and short-term variations in volatility. In this chapter, we fit a PGARCH model stated in equation (9.27) to NSM returns.

The notes on the two-speed model apply more directly to sector- and company-specific stocks and will therefore be used in future work on NSM characterisation devoted to these lower-level market situations. Note also that the PGARCH model in equation (9.27) is suitable for studying NSM returns volatility even at the overall market level as in this chapter, because it captures long- and short-term volatility effects due to myriad movements in the NSM caused by different market events for example news, policy uncertainties, financial reforms and global financial crisis.

In summary, the above notes on generalizations of ARCH/GARCH models give the conditions on the parameters that guarantee model stability and reliability of volatility estimates. We use these conditions in section 9.7 below to examine estimated NSM returns volatility models in the chapter and identify more suitable volatility models for NSM returns. We also interpret the resulting model parameters in terms of their implications for volatility persistence, asymmetry or leverage in NSM returns. In view of the interpretations, we recall the following meanings associated with GARCH model components and parameters: r_t denotes NSM return from time t-1 to t. Given investors' knowledge of all relevant variables for determining returns up to time t-1, including the values of past returns, the expected return and volatility to the investors are the conditional return and volatility given this information set denoted by $(\mu_t \mid \Omega_{t-1})$ and ($\sigma_t^2 \mid \Omega_{t-1}$), the unexpected return at time t is $\varepsilon_t \equiv r_t - \mu_t$. In this chapter, this error term is conceived of as a collective measure of news at time t. A positive value of the error term equivalent to an unexpected increase in return connotes the arrival of good news, while a negative value equivalent to an unexpected decrease in returns connotes the arrival of bad news. Also, a large absolute value $|\varepsilon_t|$ signifies 'big' and highly important news in any direction in the sense that it yields a large unexpected change in returns, Engle and Ng (1993, p. 1751), Bekaert and Wu (2000). Hence, in general GARCH models incorporate effects of current and recent news and previous volatilities (older news) in their measurement of conditional means and variances of financial quantities of interest in a study. As mentioned earlier in this chapter, volatility persistence measures how long these effects last and volatility asymmetry measures the differential impact of bad news versus good news on the quantities.

9.7 Applications to modelling volatility of NSM returns

The standard practice in volatility analyses includes the following steps:

a. use of high-frequency daily weekly or monthly adjusted return data, that is, returns minus mean returns or differences in log returns of successive periods as in this chapter, Liu and Morley (2009);
b. use of summary statistics to describe the key return characteristics for different periods, including tests of normality, Shin (2005), Xu (1999), Koopman and Uspensky (2002), Aggarwal et al (2001), Rousan and Al-Khouri (2005), Asai and McAleer (2007), Wong and Cheung (2010);
c. providing visual perspectives on the observed volatilities by plotting the volatilities for each series;
d. determining optimal number of lags for the models through critical examination of autocorrelation and partial autocorrelation statistics accompanying the Ljung-Box Q statistics;
e. comparing alternative models using selected information criteria used in assessing model fitness for example Akaike Information (AIC), Schwarz Criterion (SC) and Hannan-Quinn Criterion (HQC) and log-likelihood function, Rousan and Al-Khouri (2005);

f. assessing stability or stationarity of the models and the reliability of the volatility estimates, using known results on the required parameter values and/or their sums;
g. using dummy variables as appropriate in the return and/or volatility models to isolate the effects of day of the week, month of the year, year or other external variables on the returns and volatilities, Islam and Watanapalachaikul (2005, p. 134-144), Engle and Ng (1993), Roh (2007, p. 920), Aggarwal et al (2001, p. 53), Batra (2004, p. 17), and
h. finding meaningful interpretations of model parameters in terms of volatility persistence, asymmetry or leverage, Engle and Ng (1993), Roh (2007). In this section we employ a good number of these steps, as appropriate, for our modelling objectives.

Particularly, Aggarwal et al (2001) adopt the augmented (or dummy variable) approach in estimating the volatility equation; we illustrate the volatility equation of this kind for a GARCH (1, 1) model thus

$$h_{t+1} = \omega + \beta_1 h_t \varepsilon_t^2 + \beta_2 h_t + \sum_i d_i D_i + \sum_j m_j M_j + \sum_k y_k Y_k \qquad \text{Equation 9-29}$$

where D_i, M_j, Y_k are dummy variables for days, months and years with corresponding effects on the volatility denoted by the coefficients in lower-case letters. In this chapter, following Islam and Watanapalachaikul (2005) and in the spirit of equation (9.25) above, we use the dummy variables in the returns equation thus:

$$r_t = \mu + x_t^T b_i + \varepsilon_t \equiv \mu + \sum_i b_i D_i + \sum_j m_j M_j + \sum_k y_k Y_k + \varepsilon_t \qquad \text{Equation 9-30}$$

We note that in using the model this form of the augmented model in this chapter, we have fitted fairly parsimonious models in which almost all insignificant dummy variables are eliminated and only the significant variables are reflected in the summary tables for the models as volatility factors. The parsimonious models are obtained by firstly fitting full models, progressively removing insignificant variables and refitting the models until almost all remaining variables become significant.

9.7.1 Empirical results and interpretations

9.7.1.1 Descriptive statistics

This section presents basic statistical analyses of NSM behaviour using the All Share Index (stock index) for the entire market and corresponding values of market returns from period to period. A stock market index measures the performance of the entire stock market if it is obtained for the whole market or related stocks in a market sector if it is obtained for selected stocks in the sector. For example, apart from the All Shares Index, an index can be calculated for stocks in financial services or manufacturing sectors of a market.

As shown in equation (9.31) below, a stock index can be computed by comparing the current total market value of the issued shares of the constituent stocks in a particular day t with the corresponding value on the previous day t-1 as follows:

$$I_t = \frac{\sum MC_t}{\sum MC_{t-1}} \times 100 \qquad \text{Equation 9-31}$$

where MC is the market capitalization of constituent stocks on different dates with base date $t-1$. Hence, the stock index measures the rates at which the market changes in value from day to day. A stock market return measures the relative change in stock market index from period to period and is given by:

$$R_t = ln\,(\frac{I_t}{I_{t-1}}) \times 100 \qquad \text{Equation 9-32}$$

where ln is the natural logarithm of the ratio of indexes. We display in Figure 9.1 below the NSM returns used in this study.

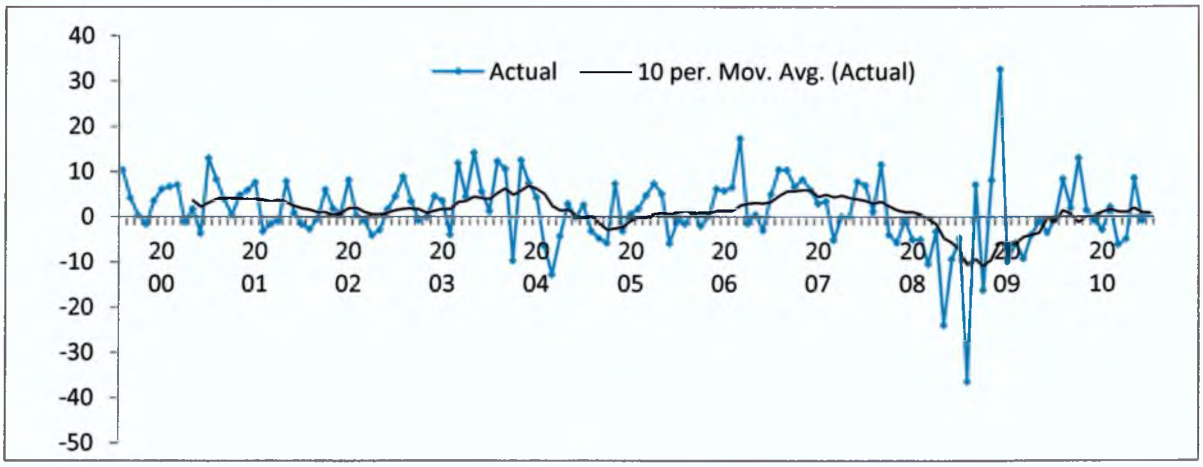


Figure 9-1 : NSM Returns with fluctuations around a 10-point moving average, 2000-2010

In order to describe the central tendency, dispersion and shapes of frequency distributions of NSM data, descriptive statistics of the NSM return residuals are obtained such as the mean, standard deviation, skewness and kurtosis. The NSM return residuals are also tested for normality using the Jarque-Bera test, widely used for testing normality of data because it incorporates both skew and kurtosis. The test statistic is given by:

$$JB = \frac{n}{6}\left(\gamma^2 + \frac{(\kappa-3)^2}{4}\right) \sim \chi^2_2 \qquad \text{Equation 9-33}$$

where n = sample size, γ and κ denote skewness and kurtosis, respectively. Under a null hypothesis of normality of return residuals the statistic follows a chi-square distribution with 1 degree of freedom each for skewness and kurtosis. So we reject normality of return residuals at 5% level of significance if the p-value of the observed value of *JB* is less than 0.05 and accept otherwise.

Understanding how the distributions of stock index and returns (residuals) vary across different periods enables us to describe the impacts of financial reforms or the global financial crisis on the NSM. For example, different values of the standard deviation for different periods indicate relative volatilities of the data for the periods. We present the key descriptive statistics of daily NSM return residuals for the overall period in Figure 9.2 below; the results for all periods are (**presented in Appendix 9.1**) summarized in

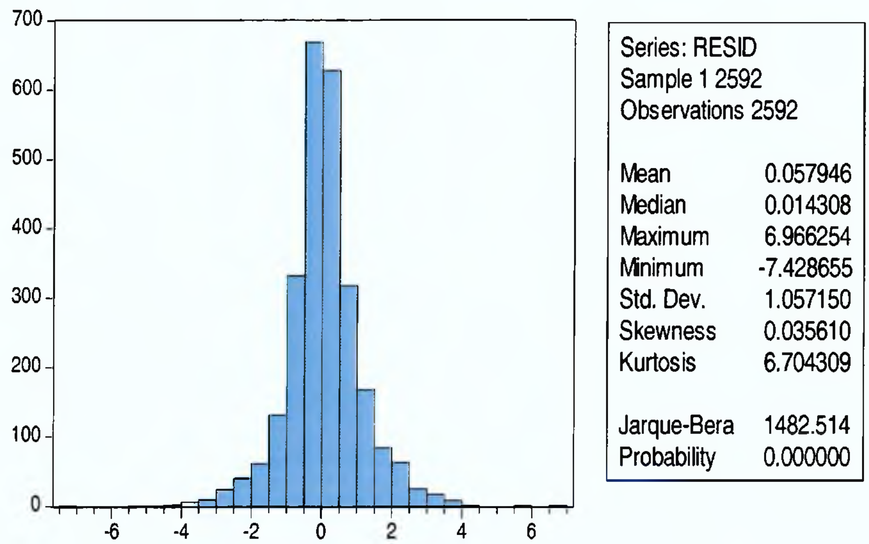


Figure 9-2 : Descriptive statistics of return residuals for the overall period (2000-2010)

Figure 9.2 shows that the residuals are fairly bell shaped to justify the use of t-distribution in the ARCH/GARCH modelling of NSM returns presented here. A closer look at Table 9.1 shows that the mean return residuals are not all zero meaning that some factors other than random fluctuations may still account for variations in returns, hence volatility. That the summary statistics for different periods are different suggests that some of the non-random influences on returns may be associated with events associated with the periods, including the bank financial reforms and the global financial crisis. For example, the post-reform skewness is nearly 5 times that of the pre-reform period.

Also, the Ljung-Box Q-statistics reject the null hypothesis of no serial correlations in the errors at all lags up to 10 for all the periods ($p = 0.0000$); see Appendix 9.1 for details of these tests for all lags since only lag 10 results are displayed in Table 9.1. This fact indicates the existence of time-varying volatility (volatility clustering) in NSM returns, Rousan and Al-Khouri (2005, p. 110). The Ljung-Box statistics show decay behaviour in the correlations and partial autocorrelations such that the low-order correlations are much larger than the higher order ones. This supports the use of first order GARCH models in this chapter to analyse the volatility dynamics in the NSM. Also, these correlations are significant up to so many lags in the past (up to lag 10 as stated). This suggests that return volatilities are persistent so that shocks in the NSM due to market events, financial policies and other influences are long-lasting.

In sum, the above results warrant the kind of detailed assessment of NSM volatility undertaken in this chapter. As noted in the introduction, the aim of volatility modelling is to ascertain the underlying volatility structure (persistence and asymmetry) and the contribution of days, months and years to the volatility.

Table 9-1 : Descriptive statistics of return residuals for different periods

Statistic / Periods	Mean	Std. dev	Skewness	Kurtosis	Jarque-Bera/Probability	AC(10)	PAC(10)	Q-Stat	Obs.
Overall 2000-2010	0.0579	1.0572	0.0356	6.7043	1482.514 (0.0000)	0.023	-0.002	795.18	2592
Pre-reforms 2000-2004	0.0592	1.0380	-0.0620	9.3582	1904.120 (0.0000)	0.052	-0.003	208.44	1130
Post-reforms 2005-2010	0.0615	1.0750	0.1567	4.7572	194.0832 (0.0000)	0.036	0.005	638.35	1462
Post-reforms/Pre-crisis 2005-July 2007	0.0904	0.8377	0.1311	6.1636	260.7531 (0.0000)	0.049	-0.031	212.29	621
Post-reforms/Post-crisis August 2007-2010	-0.0144	1.2385	0.1173	3.8569	27.6610 (0.0000)	0.017	0.026	408.93	481

The results for skewness, kurtosis and normality show that daily NSM return residuals are generally slightly skewed, leptokurtic and non-normal. Compared to developed markets which have significant negative skewness, the NSM returns show positive skewness which is characteristic of emerging markets, Aggarwal et al (2001). The returns distributions are significantly non-normal and have fat tails as seen in the significant Jarque-Bera statistic ($p = 0.0000$). Hence, the t-distribution is more suitable for modelling NSM return volatilities as in EViews, Bollerslev (1986).

As expected, measured by the standard deviations, volatility is very high in the NSM as a pre-emerging market. The volatility values are 105.72%, 103.0%, 107.50%, 83.77% and 123.85% for the periods, taken in descending order in Table 9.1 from overall period to post-reform/post-crisis period. Note that while the pre-reform and post-reform volatilities are approximately the same value, suggesting that the bank reforms do not affect NSM volatility appreciably, the volatility has increased remarkably before and after the financial crisis (an increase of about 40%). Hence, the global financial crisis has affected NSM volatility; see Figure 9.1 above which shows wilder fluctuations in NSM returns in NSM return residuals or years 2003-2004, 2006-2006 and 2008-2009 which bracket the financial reforms and global financial crisis.

9.7.1.2 Results from GARCH estimation

We have used five different GARCH-type models described in Section 9.6 above to explore NSM return volatility, namely GARCH (1,1), EGARCH (1,1), GARCH-M (1,1), GJR-GARCH (1,1) and PGARCH (1,1). The models will hopefully capture inherent volatility persistence (using $\alpha + \beta$), asymmetries in NSM returns (using γ or δ), and contributions of current (using α) and old news (using β) to volatility, to possibly different degrees. The benchmark GARCH (1,1) model assumes symmetry in the effects of bad and good news on NSM volatility.

Table 9.2 presents the GARCH (1,1) model estimation results for the whole study period 2000-2010. The table shows that month 9 (September) and years 2000, 2009 and 2010 are significant at 5% level as an additional influence on returns and volatility. This is not unexpected given that these years coincide with the global financial crisis which induces additional investor caution and uncertainties in investment decisions. The September effect is obviously associated with the impact of September 2008-2010 events during the financial crisis. The year 2000 effect may be associated with possible changes in the national macroeconomic conditions over time, particularly in the period preceding the 2004 bank restructuring and the 2007 global financial crisis.

In terms of the variance equation and model attributes, we note that $\omega = 0.1485$, $\alpha = 0.5322$ and $\beta = 0.4265$. Hence, $\alpha + \beta = 0.9587$ is very close to 1 indicating that volatility shocks in the NSM are strongly persistent. Again, a comparative look at the alpha and beta parameters show, respectively, that current and old news have strong impacts on NSM return volatility. Also, the estimate of unconditional variance of NSM returns from this model is given as $\hat{\sigma}^2 = \omega/(1-\alpha-\beta) = 0.1485/0.0413 = 3.5956$. Finally, since $\alpha + \beta = 0.9587 < 1$ the model is stable so the model parameters and estimates are reliable. In other words, the model is weakly stationary.

Table 9-2 : Estimation of the GARCH (1, 1) model results for 2000-2010 (as in Appendix 2a)

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/20/12 Time: 22:17
Sample: 1 2592
Included observations: 2592
Convergence achieved after 21 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.046870	0.017244	2.718017	0.0066
M9	-0.159737	0.052871	-3.021258	0.0025
Y00	0.134817	0.049754	2.709654	0.0067
Y08	-0.340547	0.052478	-6.489350	0.0000
Y09	-0.204604	0.058367	-3.505491	0.0005
	Variance Equation			
C	0.148469	0.018004	8.246415	0.0000
RESID(-1)^2	0.532234	0.059009	9.019600	0.0000
GARCH(-1)	0.426540	0.035879	11.88835	0.0000
T-DIST. DOF	5.563568	0.570934	9.744672	0.0000

R-squared	0.012361	Mean dependent var	0.059927
Adjusted R-squared	0.009302	S.D. dependent var	1.071256
S.E. of regression	1.066261	Akaike info criterion	2.565079
Sum squared resid	2936.648	Schwarz criterion	2.585427
Log likelihood	-3315.342	Hannan-Quinn criter.	2.572453
F-statistic	4.041098	Durbin-Watson stat	1.029714
Prob(F-statistic)	0.000087		

The above model characteristics are summarized in Table 9.3 below for the overall period. (Similar results for all the models and study periods are presented in Appendixes 9).

Table 9-3 : GARCH model specifications and performance characteristics for the overall period

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
Overall 2000-2010	GARCH(1,1)	September, 2000 2008, 2009	0.1485	0.5322	0.4265	-	-	Reliable, Persistent volatility, $\alpha + \beta = 0.9587$, strong impact of current and old news on volatility, no asymmetric effects, persistent volatility	2.5651	2.5854	2.575	-3315.342	
	EGARCH(1,1)	2008, 2009	-0.5284	0.6604	0.8249 < 1	0.00	0.00	Model is stable with same results as above	2.5704	2.5885	2.5770	-3323.258	

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
	GARCH-M(1,1)	September,2000, 2008, 2009	0.1484	0.5248	0.4313	0.00	0.00	$\alpha+\beta=0.9561$ Same results as with GARCH (1,1) but slightly less volatility persistence	2.5620	2.5847	2.5702	- 3310.413	GARCH-M(1,1) model
	GJR-GARCH(1,1)	September 2008, 2009	0.1475	0.5937	0.4319	-0.1545		$\alpha+\beta+\gamma/2$ $=0.9484<1$; model reliable with highly persistent volatility	2.5658	2.5861	2.5731	-3316.243	
	PGARCH(1,1)	September, 2000, 2003, 2008, 2009	0.1529	0.4767	0.4723			$\alpha+\beta=0.9490$ <1; model reliable with persistent volatility; good impact of new and old information on volatility	2.5626	2.5896	2.5725	-3309.157	

9.7.2 Discussion of GARCH modelling results in Table 9.3 and Appendix 9

Starting with the return equations, the dummies for days, months and years are selectively significant implying that these factors contribute to NSM volatility for the models in which they are significant. For the overall period as a baseline, most models identify years 2008**, 2009** and September ** ($p < 0.01$) as significant influences on returns. The GARCH (1,1), GARCH-M (1,1) and PGARCH (1,1) models curiously identify year 2000** ($p < 0.01$) as highly significant. This result may be associated with some market event or policy in the year which transmits long-lasting volatility shocks into the NSM. Understandably, the years 2008-2009 effects are due to the global financial crisis. The PGARCH (1,1) model also identifies year 2003 as ($p<0.01$) as highly significant. This result may due to the fact that this year precedes the 2004 introduction of bank reforms in Nigeria with accompanying adjustments on investor behaviour impacting the volatility. That September is consistently identified across almost all the models in the post-reform period is indicative of a September anomaly or volatility effect, possibly associated with financial policy and/or reporting rules which require further investigation

From the volatility (or variance) equation for the same overall period, all models are reliable and manifest volatility persistence with appropriate parameter sums 0.9587, 0.9561, 0.9484 and 0.9490 which are almost equal. The models show no asymmetric effects of bad and good news on NSM return volatility. The GJR-GARCH (1,1) model manifests a significant asymmetric volatility effect ($\gamma = -0.1545$, $p = 0.0355 < 0.05$). In all the models the coefficients that represent the impacts of current and old news on volatility, α and β, respectively, are highly significant. These results show that volatility in the NSM is strongly affected by the impact of current and old news transmitted into the market. Particularly with respect to the two models used in testing for asymmetric effect due to bad and good news, the EGARCH (1,1) and GJR-GARCH(1,1) models, the persistence of volatility given by $\beta = 0.8249$ for EGEARCH(1,1) model and $\alpha + \beta + \gamma / 2 = 0.9484$ for GJR-GARCH(1,1) model is reasonably high. On the basis of these empirical results, the NSM is not strongly asymmetric so that good and bad news have almost the same impact on future volatility.

The high volatility persistence levels mean that shocks transmitted through the NSM by market news, financial reforms, monetary and fiscal policies, global financial crisis and related volatilities in key market sectors for example oil price volatility, affect NSM return volatility for a long time in the future, Adamu (2008), Ezepue and Solarin (2008). This is consistent with results in other emerging markets for example Amman Stock Exchange in Jordan and also India, Korea, Malaysia, Philippines, Taiwan, Thailand and Argentina, Rousan and Al-Khouri (2005), Shin (2005). Given Nigeria's dependence on oil, it is important to explore in future work the link between NSM volatility, oil price shocks, exchange rate fluctuations, and the macroeconomics of Nigeria, Adebiyi et al (2009), Aliyu (2009a and b).

For the pre-reforms period (2000-2004), the results are summarized in columns 3-9 of Table 9.3. The volatility persistence parameters for the models, taken in descending order in which the models are presented in the table, are 0.8468, 0.7987, 0.8402, 0.8588 and 0.8653. These values are less intense than corresponding values for the overall period. Again, there are no significant asymmetric effects in the EGARCH (1,1) but there is a significant gamma asymmetric volatility measure for the GJR-GARCH(1,1) model ($p = 0.0221 < 0.05$).

In sum, while the pre-reform period resembles the overall period in volatility features, there is some indication of asymmetry associated with uncertainties related to the introduction of bank reforms in 2004. It is also instructive that with respect to the returns equation all the models identify the months of March and July and the year 2003* (a year before the 2004 reforms) as a significant influence on NSM returns. This fact shows that there is a one-year lead in the effects of financial reforms beginning to impact the NSM, due probably to anticipatory investor behaviour and expectations formation. These behavioural aspects require further studies within the systematic characterisation of the NSM discussed in this chapter.

For the post-reform (2005-2010) period, most of the results in the overall and pre-reform periods are maintained and detailed in Table 9.3. We look for any intriguing differences between periods as follows. The volatility persistence parameters are 0.9921, 0.8449, 0.9853 and 0.9809 and 0.9811 for the five models. Compared to the preceding periods, these values indicate far more intense volatility persistence meaning that the introduction of bank reforms has increased volatility persistence in the NSM.

This result is to be expected since the reforms stir up keener anticipation of market movements on the part of investors, which reinforces the effects of reforms on NSM return variations.

Generally, the model coefficients are similar for the (symmetric) models showing that a benchmark GARCH (1,1) or GARCH-M(1,1) model could suffice for modelling NSM volatility in this period. The GJR-GARCH(1,1) model accepts the null hypothesis of no asymmetric effect of bad and good news on NSM volatility (p = 0.4676) thus confirming the fact that the above benchmark symmetric models are good candidate models for analysing NSM volatility in the post-reform period. For the returns equation in the post-reform period, the models identify years 2005, 2006, 2007, 2009 and 2010 as influential years in NSM returns. The significant monthly influences are August, September, October and November with September identified by all the models. To separate out the confounding effects of the global financial crisis on NSM volatility, we discuss below the post-reforms pre- and post-crisis volatility behaviours.

For the post-reforms pre-crisis period (2005-July 2007), almost all previous model results hold, with the following departures noted. Volatility persistence parameters are less intense compared to pre-reforms period with the parameter values of 0.9148, 0.8578, 0.9246, 0.8995 and 0.8211. These results are again very close for the symmetric models and thus re-confirm the versatility of benchmark GARCH-M (1,1) models in analysing NSM volatility. The GJR-GARCH(1,1) model shows barely significant asymmetric effect due to anticipated bad news from the financial crisis ($\gamma = -0.2254, p = 0.05$).This is likely to be due to a confluence of reforms and crisis effects and shows that the crisis really built up in years 2005 and 2006 which precede the break-out year 2007 when the crisis 'blossomed'. The models identify Friday, August and years 2005 and 2006 effects.

A policy implication of these results is that continual monitoring of NSM key characteristics including volatility should be maintained by appropriate research and policy organizations in Nigeria so that signals to possible shifts in the characteristics could be picked up at most two years before their full manifestation on the economy. The concerned organizations in mind include the research department of the CBN, finance and economics research units in Nigerian universities and equivalent units in the NSE, the SEC, banks, stockbrokers, and investment firms.

In sum, for this period, the volatility models are reliable; there is strong impact of current and old news, and evidence of high volatility persistence in the NSM.

For the post-reform post-crisis periods (August 2007-2010), we observe the following features:

a. far more intense volatility effects showing no daily effects for all the models;
b. significant August-December effects for most models; and
c. highly significant years 2007, 2009 and 2010 effects. These volatility effects are presumably due to more intense policy moves in light of the financial crisis. The significant volatility shocks transmitted during 2007 confirms 2007 as a break-out point in the crisis which built up gradually from the years 2005 and 2006 and continued up and till 2010.

The inability of the GARCH models to pick up year 2008 as a significant influence on volatility and returns is possibly due to the fact that containment policies for the crisis were intensified between 2007 and 2008 and appear to have calmed the febrile global and Nigerian financial markets sufficiently during 2008. It should be noted that ARCH type effects are usually observed if there is a significant fall in the value of a stock or index, which was the case for many stocks during the financial crisis. Hence, the observed ARCH effects may be leverage effects.

The significant yearly effects in 2009 and 2010 may also be connected with further weakening of bank balance sheets and near collapse of banks in Europe (Spain, Portugal and Germany, for example), US (Bear Stearns, Lehman Brothers), Nigeria (Intercontinental Bank plc, Oceanic Bank, Bank PHB, for example), and other developing economies where financial institutions started withdrawing investment funds in order to strengthen their domestic positions.

We emphasize that further research on sector- and company-specific indexes and returns should be conducted as part of wider NSM characterisation studies, in order to ascertain whether these models or higher order forms of the models apply to these levels, and for related financial quantities such as interest rates and exchange rates.

9.7.3 Which models fit the data best?

In order to examine which of the five models used in this chapter fit the data best across the five periods, we look at the Akaike information criterion (AIC) (or the Schwartz criterion (SC) and the Hannan-Quinn criterion (HQC)), together with the log-likelihood (Log-L) statistics, Shin (2005, p. 35-41), Rousan and Al-Khouri (2005, p. 105-115). The AIC, SC and HQ statistics are fairly similar across the models and periods. We use the AIC and Log-L statistics to set up a model-fitness contest summarised in column 14 of Table 9.3 (and similar tables in Appendix 9). The best fit models are those with minimum AIC and maximum Log-L statistics and, respectively for the five periods, are: overall period GARCH-M (1,1) model; pre-reforms period GJR-GARCH (1,1) model; post-reforms period GARCH-M (1,1) model; post-reforms pre-crisis period GJR-GARCH (1,1) model; and post-reforms post-crisis period GARCH-M (1,1) model. Hence, the GARCH-M (1,1) model wins the contest overall. Understandably, the asymmetric GJR-GARCH (1,1) model is the best fit model for the two financial reform/crisis periods associated with significant investor and policy moves (pre-reforms 2000-2004 and post-reform pre-crisis 2005-2007).

The fact that the best model reverts from the GJR-GARCH (1,1) model in these reform/crisis periods to the winning GARCH-M(1,1) model in the post-reforms post-crisis period suggests this model as the benchmark model for general NSM characteristics in future studies, to be complemented by suitable asymmetric models for periods of relatively pronounced policy moves. A look at Appendix 9-7 shows that the suggested models for this idiosyncratic analyses are the GJR-GARCH(1,1) and EGARCH(1,1) models. Note that the GARCH(1,1) model fails to make the model performance contest and is not reliable for the August 2007-2010 period with $\alpha + \beta = 1.0047 > 1$. Consequently, we suggest that future studies of NSM behaviour concentrate attention on the other models ignoring the attractions of the basic GARCH(1,1) model as a more parsimonious model.

Technically speaking, the superiority of the GARCH-M(1,1) model for NSM volatility modelling compared to the GARCH(1,1) model indicates some evidence of returns predictability in the NSM, since the model posits a relationship between returns and risk which is fundamental to financial risk management and portfolio analyses. This shows that investors may likely benefit from arbitrage opportunities associated with agile asset allocation and fund management schemes in the NSM, subject to a favourable balance between transaction costs and net gains from the opportunities.

To reiterate earlier remarks, it would be interesting in further work on NSM characterisation to fathom to what extent these results persist in finer sector- and company-specific studies of NSM behaviour, for example in the oil and gas, banking and financials, and telecommunications sectors. We pursue these discussions in Chapter 10 of the thesis on the implications of the results for political economy and stock market development considerations.

9.7.4 Financial econometric modelling and applications for systematic NSM characterisation

The application of suitable financial econometric models for financial market analyses to the NSM is the key contribution of this thesis to knowledge. We conclude from the results in the thesis that it is feasible to select a set of suitable empirical finance models which financial analysts and policy makers can use as starting points in exploring emerging issues in financial markets, with a special emphasis on African financial markets. For example, we have shown that benchmark models which should be used in further studies of the NSM should include both symmetric and asymmetric volatility models of the ARCH-GARCH types for example GJR-GARCH (p,q), GARCH-M(p,q), EGARCH(p,q) and PGARCH (p,q) models.

We have also shown that, consistent with findings in the literature, lower-order forms of these models (p=q=1) provide reliable and robust results for the NSM volatility returns. Naturally, as shown in Chapters 5-6 of this thesis, these models should be accompanied by descriptive statistics and univariate time series analyses which reveal the baseline empirical characteristics of the financial systems of Nigeria and other African markets.

9.8 Future research

For future research, therefore, more in-depth studies of volatility and other market issues - market efficiency, bubbles, anomalies, predictability and valuation - are needed at sector and company levels, Fox (2009), Cuthbertson and Nitsche (2005), Koller et al (2010), Keane (1983), Lo and Mackinlay (2002). For the volatility modelling, different order levels (p,q) of the models and lag times used in the studies could be determined using detailed statistical tests for different sub-sectors of the Nigerian financial markets for example bonds, equities and money markets. Of immediate interest are the financial, telecommunications, oil/gas, agriculture/commodities, and manufacturing sectors, earlier mentioned in this chapter.

Future studies could explore the generating stochastic processes for asset prices in these sectors, in the context of moderating economic variables for example interest rates, inflation rates, consumer price index, and exchange rate fluctuations, Adebiyi et al (2009), Aliyu (2009a,b), Umar and Kilishi (2010), Knight (2011).

Knowledge of these processes should be leveraged in more technical applications, say, on traditional versus algorithmic trading, using combinations of real-time historical and market/non-market data to explore ideas such as alpha risk/CAPM models, quantitative/qualitative risk models, transaction risk models, portfolio construction, and related behavioural finance perspectives, Knight (2011). The robustness or otherwise of normal-based inference in these analyses should also be considered and attempts made to fit matching distributions other than the normal distribution to the key market variables in the NSM and other African markets, McDonald (1996).

Studies of a more qualitative nature on, say, investor behaviour should be conducted for insights on speculative behaviour, Ezepue and Solarin (2008), Forbes (2009) and Greenspan (2008). Other qualitative studies should include fuller applications of the empirical findings in policy-related work on stock market development, overall economic development of Nigeria, and other African countries, AFDB (2007), Stiglitz (1993), Greenspan (2008).

Both for the overall market and finer levels of study, volatility and anomalies could be studied using formal non-linear complex dynamic chaos models in order to assess the chaotic behaviour of the NSM. Related to these analyses, econophysics models could also be applied including for examples stochastic resonance models and other simulation-based models with theoretical foundations in statistical physics, Bouchaud and Potters (2003), Mantegna and Stanley (1999), Voit (2005), Sinha et al (2010), McCauley (2004), Sornette (2004), Bertram (2005), Preis and Stanley (2011). Deeper empirical studies of the NSM and other African markets could be conducted using stochastic volatility models in the contexts of market microstructure analyses and asset allocation, Bekaert and Harvey (2002), Peng et al (2005).

The above suggestions for further work add up to a need for a new economics in Nigeria underpinned by systematic characterisation of the Nigerian financial markets (the NSM, bond and money markets). This need is schematized in Figure 9.3 below which is adapted from Ezepue and Solarin (2008).

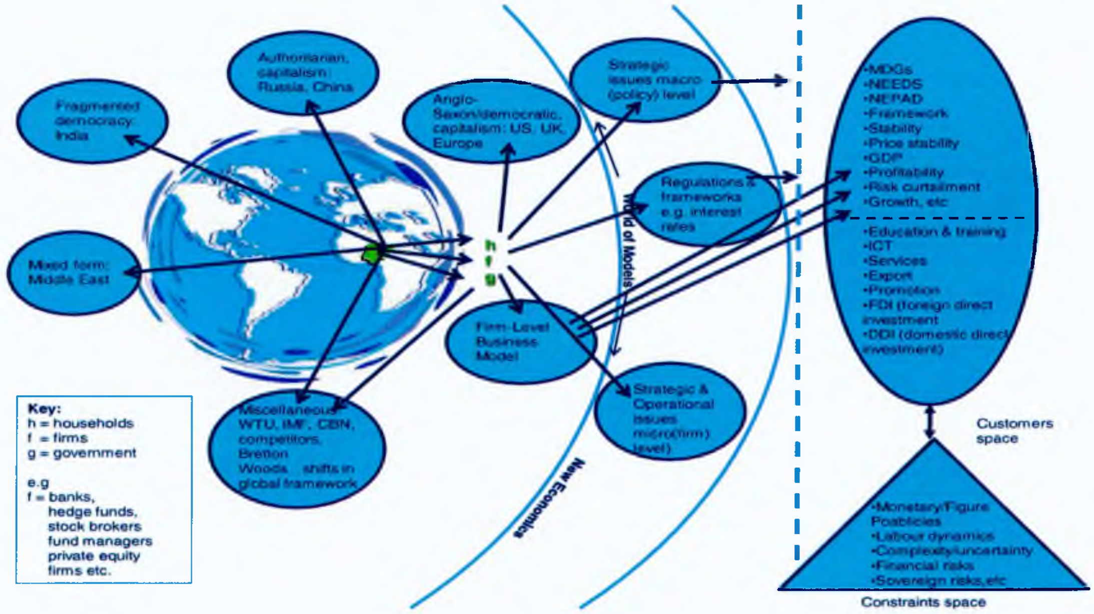


Figure 9-3 : Policy Analysis and Decision Spaces for Economic Agents/Market Participants in a Globalized Financial World (Adapted from Ezepue and Solarin 2008)

The figure shows the global setting in which finance and political economy issues in Nigeria and other emerging African markets should be considered, in order to enhance sustained growth and competitiveness. It calls for a New Economics in which fiscal, monetary and related macroeconomic policies enable households, firms and governments to optimize their investments in Nigeria, Africa and other regions of the world, within an oftentimes changing global financial architecture. The political economy issues of interest include the elements listed in the large oval-shaped outcome space in the figure for example price stability, GDP growth, profitability of market participants, risk curtailment, and achievement of national and global development goals, such as the National Economic Empowerment and Development Strategy (NEEDS) and the United Nations Millennium Development Goals (MDGs).

In this schematic, the World of Models which market participants use to reach the above mentioned goals is circumscribed by the macroeconomic status quo, financial and institutional regulations set by Central Bank of Nigeria (CBN), the Securities and Exchange Commission (SEC), for example, and firm-level strategic and operational issues. The overall outcomes, as depicted in the constraints space, are subject to controls set by monetary policies, labour dynamics, financial risks, and sovereign risks.

The above insights show that managing the kind of chaotic dynamics exhibited by the Nigerian economy in Figure 9.1 and revealed in the time-varying volatility of the NSM in this chapter requires a deeper characterisation of the NSM in light of the above interconnections. The financial reforms, bank restructuring schemes, and stock market development policies set by SEC and the Nigerian Stock Exchange (NSE) should be played out against such a characterisation.

From the perspective of this research, therefore, key NSM characteristics such as market efficiency, bubbles, anomalies, volatilities, valuation and predictability, and their implications for investment risks, capital growth, and stock market performance should be continually monitored against changing policy contexts. This should be at overall market level and sector-/company-specific levels, Ezepue and Solarin (2008). For example, these characteristics should be studied for the banking sector and specific banks in the sector using key variables such as interest rates, share prices, price/earnings ratios, inflation indices, consumer price index, returns, and other macroeconomic indicators, Fama (1991), Barucci (2003). The probability distributions of (adjusted) returns in the sector and component firms should be characterised for their tail behaviours relative to, say, the normal distribution and other common distributions in statistical finance for example the log-normal and generalised gamma distributions, McDonald (1996).

For this kind of systematic characterisation, research results on firm performances conducted through fundamental analyses should be produced as complements of data going into the stochastic models used in the characterisation work. Hence, a meta-analysis of empirical finance and financial economics papers produced by researchers on the Nigerian financial system should be conducted from time to time, and their implications for economic development, competitiveness, profitability, portfolio management, risk management, and stock market development distilled by disciplinary experts, Ezepue and Solarin (2008), Osinubi (2004), Okpara (2010). Perhaps, this is the kind of research activity anticipated by the AFDB (2007) call for research proposals on Financial Services and Economic Development in the SANE countries of Africa. This research contributes to the empirical finance strand of the systematic characterisation discussed in this section.

Finally in this section, we propose a pooling together of Nigerian academics in finance, mathematics, statistics, and economics, say, and related financial services professionals into a university-industry research consortium capable of producing the different strands of research results which the above mentioned systematic characterisation requires.

9.9 Summary and Conclusion

This chapter uses parsimonious (low-order) GARCH models to explore the volatility of overall market returns in the NSM in light of financial reforms (2004 bank restructuring) and the 2007 global financial crisis. The key findings are as follows:

a. identification of suitable and best-fit models for NSM volatility for different periods in the study, namely, the overall (2000-2010), pre-reform (2000-2004), post-reform (2005-2010), post-reform pre-crisis (2005-July 2007), and post-reform post-crisis (August 2008-2010);
b. examination of the implications of the results for stock market characterisation and development and welfare economics of the Nigerian financial system (institutions and policies), particularly the connections between NSM volatility and economy-wide influences for example oil price volatility, exchange rates, et cetera;
c. clarification of the nature of further research in volatility modelling which will benefit investment analysts, academics and policy makers;
d. identification particularly of the significant factors associated with return volatility in the different periods for example the days, months and years which contribute to the mean returns component of the models; these results triangulate to some extent our observations about anomalies and bubbles in Chapters 8 and 7, respectively;
e. the fact that financial reforms and the global financial crisis significantly exacerbated NSM volatility by making more days, months and years significant influences on volatility compared to the overall periods and pre-reform periods.

With respect to the objectives and research questions of interest in this thesis, we note that the chapter critically reviews the key literature on different aspects of volatility which will benefit future research, especially at financial market sector and company levels (**Objective 1**). As mentioned above, it identifies suitable GARCH models for volatility analyses in the Nigerian financial system (**Objective 2**), and examines in some detail the policy implications of the results (**Objective 3**). Finally, it confirms that there are significant volatility effects in the NSM (**RQ 4**).

For a look ahead, empirical development finance techniques such as explored in this chapter need to be applied to main sectors of the NSM, the Nigerian financial system and other emerging African markets for example the Libyan Stock Market, especially in periods spanning key events such as financial reforms and global financial crisis. The results of the analyses in the chapter reveal that the NSM does not show the characteristics of a sound Nigerian financial system, a reality that is consistent with many studies on emerging financial markets earlier referred to in the chapter.

All features of the NSM studied, from the overall market index/returns perspective, show that it is weak-form inefficient, with relatively poor and sometimes asymmetric information flow as revealed through the volatility results and models. Substantial statistical evidence in Chapter 6 of the thesis reject the null hypothesis of the error process associated with NSM returns being white noise in the periods studied. The notion of weak-form market inefficiency is supported by evidence of anomalies and volatility in Chapters 8 and 9. Even though the techniques of duration testing used in Chapter 7 does not confirm the existence of rational bubbles at the overall market level, we suspect, given the severe market failures in the bank sector and the stock market collapse of 2010-2011 in Nigeria, that sectorial bubbles may exist in the NSM. This should be investigated in further work as already suggested.

Overall, our findings suggest the existence of significant market imperfections and failures in the Nigerian financial system. However, the explanations and policy implications of these imperfections can only be convincingly understood within the context of institutional and macroeconomic foundations of the system, as discussed in the foregoing notes and also Chapter 2 of the thesis.

Suitable monetary, fiscal and regulatory policies are germane for the development of an efficient and appropriate financial system in Nigeria which can support the key aims of the Nigerian Financial Services Strategy (FSS 2020). The emphases of these policies should be on efficient information management, allocation of resources, macroeconomic stability, and economic development. As argued in this study, the policies should be continually underpinned by good empirical analyses such as discussed in this thesis.

We offer through the schematic and notes around Figure 9.3 broad considerations which should be borne in mind in the empirical finance work subsumed under the systematic characterization of the NSM and other emerging African markets.

Finally, Chapter 10 of this thesis pulls our findings together by linking the results on market efficiency, bubbles, anomalies and volatility to stock market characterisation and development. It particularly explores the implications of the results to welfare economics and economic development of Nigeria. The ideas developed in the chapter are also applicable to other emerging African markets.

CHAPTER 10: MAIN RESULTS OF THE RESEARCH AND SUGGESTIONS FOR FURTHER STUDIES

10.1 Introduction

This study applied some statistical and financial econometric methods to investigate the behaviour of the Nigerian Stock Market (NSM).

The NSM was established in 1960 as the Lagos Stock Exchange. It operated in 1960 with 19 securities listed for trading. As of March 2007, NSE has 283 listed companies with a total market capitalization of about N15 trillion ($125 billion). However, the number of listed companies in the market fluctuated between 195 in 1999 and 238 in July 2011. In 2004 the Nigerian Government lunched financial reforms in order improve the performance of the banking sector and the overall financial system. Also the NSM and the Nigerian financial system were affected by the 2007 global financial crisis.

This research is the first study that investigates the empirical characteristics of the NSM based on four key issues, namely market efficiency, bubbles, anomalies and volatility, especially in light of the effects of financial reforms and the global financial crisis on the characteristics (hence on the performance of the market). An understanding of these empirical characteristics of the NSM is important for investment decisions on the part of investors and for stock market development and financial policy on the part of policy makers.

The research is also the first study of this nature for a developing market in Africa and therefore provides useful insights for financial planning and stock market development in other African countries.

10.2 Main Results of the Research:

The main results of the study are summarised below.

10.2.1 Market Efficiency

Using different tests of the Efficient Market Hypothesis (EMH) in Chapter 6, the empirical results generally provide evidence against the EMH in the NSM. Specifically,

a. For the daily returns data, the autocorrelation function (ACF) test shows that there is significant serial correlation in the NSM daily returns for the three periods of study (overall 2000-2010, pre-reform 2000-2004, and post-reform 2005-2010). This is confirmed by the runs test.
b. However, the runs test shows no evidence of serial correlation in the monthly returns for the pre-reform period, at the 5% level of significance ($p= 0.193$). This suggests that the NSM is less inefficient during this period compared to the post-reform period.
c. The BDS test of i.i.d. daily returns supports the ACF and runs test results by showing that the daily returns are not i.i.d., so that there is some form of dependence in the returns from day to day.
d. Similar to the runs test results for monthly returns, the BDS test of i.i.d. monthly returns for the pre-reform period shows that there is evidence of i.i.d. monthly returns at 5% level of significance for this period (for most of the dimensions used in the test). Again, this suggests that the NSM is relatively more efficient in the pre-reform period based on monthly data.

The above results show that the empirical characteristics of NSM returns may differ according to the type of data used. The results suggest that it is easier for investors to predict daily returns compared to monthly returns for the pre-reform period.

Also, insights obtained from the different tests could be applied to data from specific sectors of the market (for example, oil and gas, financials, telecommunications, manufacturing, and agriculture) in order to understand how efficient the sectors are, especially using real stock returns and other financial indicators in the economy such as interest rates, consumer price index, and P/E ratios.

Finally, the overall inefficiency of the NSM in pre- and post-reform periods may be due to some market imperfections which should be corrected with better regulation of the market, among other policies and reforms.

10.2.2 Speculative Bubbles

Using the Duration Dependence test for rational speculative bubbles, it is shown in Chapter 7 of the thesis that rational speculative bubbles are not present in the NSM and for all the study periods. Hence, the inefficiency of the NSM and other imperfections in the market are not due to bubbles. Hence, policy makers can concentrate on using appropriate monetary, fiscal and regulatory tools to reduce market imperfections such as thinness of trading (or lack of depth in the market), low market capitalization, illiquidity of the market, lack of transparency in market transactions, and hence presence of significant abnormal returns by traders with private information.

The lack of evidence of rational speculative bubbles in the NSM is consistent with other results in Middle East and African stock markets, Yua and Hassan (2009), Olowe (1999) and Okpara (2010).

However, using overall market data limits the ability to detect bubbles in specific market sectors. For example, the recent crash of the NSM index, particularly bank share prices, may be due to sectoral bubbles.

Hence, there is need to apply different tests of bubbles discussed in the chapter to data from specific sectors of the market, particularly data that include important financial indicators used by different authors in the literature.

10.2.3 Anomalies

Using the ANOVA and Kruskall-Wallis tests in Chapter 8 it is found that there are no anomalies (or calendar effects) in the NSM for almost all the periods. That is, there are no daily (for example, Monday) and month-of-the year effects in NSM returns for the three periods. This means that the NSM returns do not show a consistent pattern of low or high relative (mean) returns for any day or month compared to others.

It is noted that even though the daily effects were not significant overall, there is some indication that there could be daily effects in the NSM as shown by the Kruskall-Wallis test for the period 2005-2010 (the post-reform period) ($p = 0.046 < 0.05$). This shows that the financial reforms and possibly the global financial crisis appear to have introduced market anomalies in the form of daily effects. These anomalies seem to be generally masked at the overall market level and could more clearly be determined in sector and company level studies in the future.

Even though there are no systematic daily or monthly anomalies overall, the analyses, however, show the different rates of contributions of the different days and months to returns, which investors can use in planning their investments into the market.

The chapter discusses different types of anomalies which could better be studied with more detailed data from specific sectors of the market. These include: the winner-loser, P/E ratio, firm-size, long-term return, and IPO anomalies.

10.2.4 Volatility

The volatility modelling of NSM returns in Chapter 9 generated several interesting results which are discussed in detail in the chapter with some implications for further work at sector and company levels. We summarise the key findings as follows:

- Identification of significant factors associated with return volatility in the different periods for example the days, months and years which contribute to the mean returns component of the GARCH models employed in the analyses
- The fact that the financial reforms and the global financial crisis significantly exacerbated NSM volatility by making more days, months and years significant influences on volatility compared to the overall periods and pre-reform periods
- Identification of suitable best-fit models for NSM volatility for different periods in the study; and
- Examination of the implications of the results for stock market characterisation and economic development of Nigeria.

10.2.5 Other results

Chapter 5 of the thesis used relevant descriptive statistics and univariate time series models to model the overall behaviour of the NSM Index and returns data during different study periods. The results show that the reforms had the potential to impact the NSM positively, but this impact was limited by the negative effects of the global financial crisis. The results show that NSM returns are skewed, leptokurtic and non-normal for daily and weekly data for all the periods, while the monthly returns are normal for the pre-reform period.

Additional to the summary statistics, the moving average and exponential smoothing models show how to identify market downturns and upturns from the NSM data and how to obtain different types of forecasts of returns and index values. Knowledge of these techniques and forecasts will inform the investment decisions of investors and the types of financial policies which will improve stock market performance.

The implications of the results for investment strategy, stock market development and financial policy in Nigeria are discussed in the chapter. Some of the discussions also apply to results obtained for market efficiency, bubbles, anomalies and volatility. Key aspects of market behaviour of the NSM (including other emerging markets of Africa) which should be considered in using the research results for investment strategy, stock market development and financial policy are explored in Chapter 2 of the thesis.

10.3 Implications for stock market characterization and welfare economics of the Nigerian financial system

We have discussed a number of aspects of current and future work on systematic characterization of NSM behaviour in the foregoing notes. In this section we link the ideas and key results of volatility analyses to welfare economics of the Nigerian financial system. Financial econometrics (or empirical finance) models typically applied to investigate the financial systems of developed and pre-emerging financial systems include six main market characteristics – efficiency, bubbles, anomalies, volatility, predictability, and valuation of asset prices. Though this study uses market-level data on the All Shares NSM index and returns and not sector- and company-specific data on indexes, share prices, returns, and interest rates, for examples, which are more suitable for exploring predictability and valuation aspects of the NSM, the results on the other four market characteristics obtained in Chapters 6-9 of this thesis suggest that NSM returns could be predictable. This requires further work in order to more solidly determine which sectors of the NSM are predictable and to what extent. In that case, research should be focused on best-fit models for predicting asset prices and returns for particular sectors and their constituent companies, Islam and Watanapalachaikul (2005).

We think that given the centrality of banks and the financial sector in general and oil/ gas sectors to the functioning of the Nigerian economy, these sectors should be prioritized in the systematic characterization of the NSM. Also, since telecommunications sector actually created a culture change in the use of technologies by most Nigerians and in view of recent digitalization of the NSM, this sector should also be prioritized in the characterization research. Next in line should be the agriculture/commodities and manufacturing sectors which are key bases for diversifying the Nigerian economy, Sanusi (2011), Olaleye (2011). In the following notes we discuss some political economy issues associated with investment decisions, financial policies and stock market development, in light of the volatility results and other market characteristics.

Welfare economics underpins the analyses and development of national financial systems and economies, and also suggests suitable policies which will aid the social welfare maximizing status of the financial system. Fry (1995) quoted in Islam and Watanapalachaikul (2005, p. 150) identifies four major differences in the characteristics of financial systems of developed and developing economies. Some of these differences, albeit under different labels, have been mentioned in our background notes on the Nigerian financial system in Chapter 2 of this thesis. Additionally, there are also some problems for stock market development associated with the financial market operations of key financial institutions in Nigeria for example banks.

These problems are again emphasized in the notes in Chapter 2 and include: market failures for example recent 2010-11failures of some Nigeria banks (Intercontinental Bank plc, Oceanic Bank plc, Afribank plc, Bank PHB plc); asymmetric information connected with corruption of senior management of the failed banks; moral hazard whereby interventions by the CBN through injection of monies into the system to prevent outright bank failures signals to bank management that government will readily help to correct their gross mismanagement of the banks; insider trading; and non-transparent and irresponsible use of shareholders' funds in unjustified risk taking, Olaleye (2011), Sanusi (2011).

As a result of the above characteristics of (pre)emerging stock markets and other associated factors for example oil price volatility, policy changes on interest rates, and exchange fluctuations, the NSM experienced high volatility in the study period 2000-2010. It is now known from the results in Chapter 9 of this thesis that the character of this volatility is conditioned by the 2004 bank restructuring and the 2007 global financial crisis. The Nigerian government should ensure the long-term stability, functionality and performance of the NSM as argued at various points in Chapter 9.

The evidence of weak-form inefficiency of the NSM in Chapter 6 of the thesis suggests that historical information on market indexes and returns can be used to predict the movement of future returns, and signifies inappropriate use of market information by households, firms and government. This situation is probably caused by the kinds of market failures highlighted above and also in Chapter 2 of the thesis. The evidence of market inefficiency further implies that the NSM is unlikely to be fully competitive. This result has implications for policy-driven efforts by the Nigerian Securities and Exchange Commission (SEC) and the Nigerian Stock Exchange (NSE) to develop the NSM along similar lines as the NYSE and the LSE for examples, Sanusi (2011), Olaleye (2011). It should be reiterated that the lessons learnt here are applicable to other emerging African markets, especially nascent markets for example the Libyan Stock Market which was established barely three years ago.

To expatiate further on the market failure idea, the NSM failures arise from costly and incorrect information and transaction costs which are exacerbated by asymmetric information and moral hazard. This fact requires that regulatory reforms by the SEC, NSE and CBN should be focused on ensuring that banks, financial institutions in general and all listed NSM firms produce honest financial reports on which investors' decisions are based. We simply recommend that these regulatory agencies adapt proven regulations from effectively managed stock exchanges for example NYSE and LSE to Nigerian and African contexts. We are happy that this appears to be the case based on recent pronouncements of the CBN, Sanusi (2011).

As discussed in Chapter 7 of the thesis, rational speculative behaviour in the NSM occurs due to lack of required market information; it is expected that market disclosure requirements that will provide such information to investors be mandated by the regulatory agencies concerned, with regards to financial reporting standards, statements of investment principles and surrounding macroeconomic influences on the financial performance of the reported firms. Also, strict adherence to capital adequacy provisions and associated Basel II/III rules, for instance, should be mandated in the NSM.

Additionally, systematic sector- and company-specific reports should be researched and reported by preferably independent investment research boutiques, in order to provide robust facts about the relative performances of different firms listed in the NSM. This will enable investors to make informed investment and risk management decisions, Ezepue and Solarin (2008), Cuthbertson and Nitsche (2008). This climate of richly available benchmark studies will facilitate a situation whereby investors in the NSM could benefit from signals about profit opportunities implicit in the investment allocation choices made by informed investors who conduct related investment research. A culture just described in which investments follow good research insights naturally allocates investment capital in the NSM to relatively more efficient and valuable assets, hence maximizing the overall welfare of market participants in the Nigerian economy. The alternative to this is that when investors trade stocks on the basis of market noise or negative information, the NSM may experience institutional and informational failures such as explored in this section. This in turn produces irrational bubbles and volatility.

Speaking, therefore, of volatility results as obtained in Chapter 9, we note that a successful stock market should possess at least two main features:

a. the stock prices and returns should not fluctuate too widely from real prices and returns, that is, from fundamental values;
b. the stock market should grow at a rapid but steady pace, Islam and Watanapalachaikul (2005).

We noted in Chapter 2 that the dynamics of the NSM relative to the Ghana Stock Market, for example, is such that the NSM exhibits rapid but very unsteady growth around an exponential trajectory, in terms of the All Share Index, for the period up to 2007, not including the whole study period for this research (2000-2010).

The results in Chapter 9 show that the underpinning volatility is complexly determined by a number of factors, some of which can be controlled by proactive financial policy, and some of which just emerge from other macroeconomic influences for example interest rates, exchange rate fluctuations, oil price volatilities, and shifts in investors' behaviours due to bank reforms and financial policies.

We stress that since the volatility results in Chapter 9 are at overall market level, further studies on NSM characterization should look at volatilities specific sectors and companies as well as inter-sector correlations. To give a specific example, a bank sector study should replicate the work in the chapter, provide comparative case studies of representative banks in the sector covering different types of banks, and also examine the inter-sector correlations and volatilities between banks/financial services sector and other sectors for example telecommunications. This will provide strong evidence base for investment analysis and portfolio management and is warranted by the recent requirements by the CBN that banks depart from the universal banking model and become more specialized, Sanusi (2011).

In addition to volatility of asset prices and returns, relevant financial stabilization and inflation control policies should be promoted by the CBN, SEC and NSE in order to contain real prices and returns within meaningful bounds, Sanusi (2011), Greenspan (2008), Fender (2012), Miles et al (2012). This will enable the NSM to effectively allocate resources and payments and foster economic development, growth and competition of and in the Nigerian economy.

To summarize the key ideas presented above, Nigerian economic, monetary and financial policies should use detailed knowledge of the key market characteristics studies in this thesis to tame emergent business cycles, control volatilities and anomalies at overall and sector/company levels, and reduce the opportunity for speculation and arbitrage in the NSM. As noted in Islam and Watanapalachaikul (2005, p. 151), 'the outcome of the EMH tests and the characteristics of institutions and markets in the Thai financial system [read Nigerian financial system] can be used in 'public policy assessment of the desirability of mergers and acquisitions, short-term and long-term regulation of financial institutions', see also Oh and Islam (2001). These results clearly apply to the EMH results in Chapter 6 of the thesis and the bubbles, anomalies and volatility results in Chapters 7, 8 and 9, respectively.

In other words, financial and regulatory policies need to be formulated to help the Nigerian financial system to produce and maintain efficient transmission of information, efficient allocation of financial and real resources, macroeconomic stability, and social welfare-maximizing economic development. These policies should include: development of effective legal system which adequately penalizes wrong practices; sound financial regulation on financial reporting, capital requirements and disclosures; and consistent fiscal and monetary policies, Sanusi (2011), Olaleye (2011), Stigliz (1993), Greenspan (2008, pp. 464-532 particularly). Financial supervision by the CBN, SEC and NSE in Nigeria should:

a. incentivise market participants to conduct effective market research and information processing; and
b. encourage financial and stock market development of the NSM. These policies are best refracted on the lenses of detailed and periodically updated characterization of the Nigerian financial system for different sub-sectors such as bond, stock and money markets.

Ultimately, the market characterization results will facilitate effective policies aimed at financial innovation, institutional development, financial engineering, corporate financial management, sound risk analysis and portfolio management, and sound corporate governance. We have discussed some of the important market characterization ideas in Chapter 9 of the thesis and expatiated on the financial econometric modelling aspects as well.

10.4 Summary of contribution of the research to knowledge

This study provides a comprehensive analysis of the NSM which is considered as one of the four largest stock markets in Africa. The study therefore critically explores the literature on stochastic and financial econometric models useful for studying stock market dynamics in (developing) financial markets (**Objective 1**).

The study also explores the suitability of different models for analysing key characteristics of stock markets for example market efficiency, bubbles, anomalies and volatility. The data requirements and assumptions for the different tests are examined and suggestions for further work on the issues in specific sectors of the market are made (**Objective 2**).

As discussed in the various chapters and summarised above, the study discusses the implications of the observed characteristics of the NSM for investment strategy, stock market development and financial policy, at least from an overall market perspective (**Objective 3**).

The results and suggestions are potentially useful to: policy makers and management of the NSM in designing policies to enhance performance of the NSM; investors and analysts stock market who will use the results as baseline characterization of the NSM for investment purposes; and academics, as a starting point for more detailed work on stochastic and empirical finance modelling of stock markets at individual firm and sectoral levels.

10.5 Suggestions for further study

- The emphasis of this study is on exploring key characteristics of the NSM using overall market data. As suggested above and specifically in the key chapters on the market characteristics, further studies should apply the models and other approaches discussed in the literature to specific firms and market sectors. This will require additional data on economic indicators which were not available for this study for example interest rates, P/E ratios, exchange rates, firm-level stock prices, consumer price index, etc.
- It would be worthwhile to survey the opinions of investors, policy makers (including NSM and NSE staff) regarding the implications of these lines of research for stock market development and financial policy in Nigeria.
- The models used in this research and indicated lines of research into the different models and market sectors should be applied to other emerging markets of Africa. For example, the research should be replicated for the Libyan Stock Market, which was newly established in 2006, in order to inform its performance.
- Due to the difficulty in obtaining different kinds of data, some important issues such as predictability and valuation were excluded from this study. These issues are particularly relevant for valuing and predicting specific stocks and sectors. Hence, we strongly recommend an extension of the research to firm- and sectoral-level analyses with particular emphases also on valuation and predictability of asset prices and returns. To reiterate an earlier example in the banking sector, the models should be applied to the overall sector with a comparative case study of a particular bank, to show how that bank performs in asset prices, share prices and returns relative to similar banks in the sector.

- Finally, future work on NSM characterisation and similar work in other components of the Nigerian financial system should particularly examine all areas of further work highlighted in the various chapters of this thesis, and should aim to develop not only rigorous aspects of the models highlighted in the literature but also explore the implications of the research results for investment analysis, financial policy, financial market development, and economic development. Particularly, such research should aim to provide continuing guidance to investors and policy makers on emerging developments in the financial markets such as introduction of new trading platforms in the NSM, financial engineering tools and financial assets, commodities trading, and private equity. For this guidance, particular emphasis should be placed on the policy priorities of the CBN and SEC articulated in Chapters 2 and 9 of the theses mainly.

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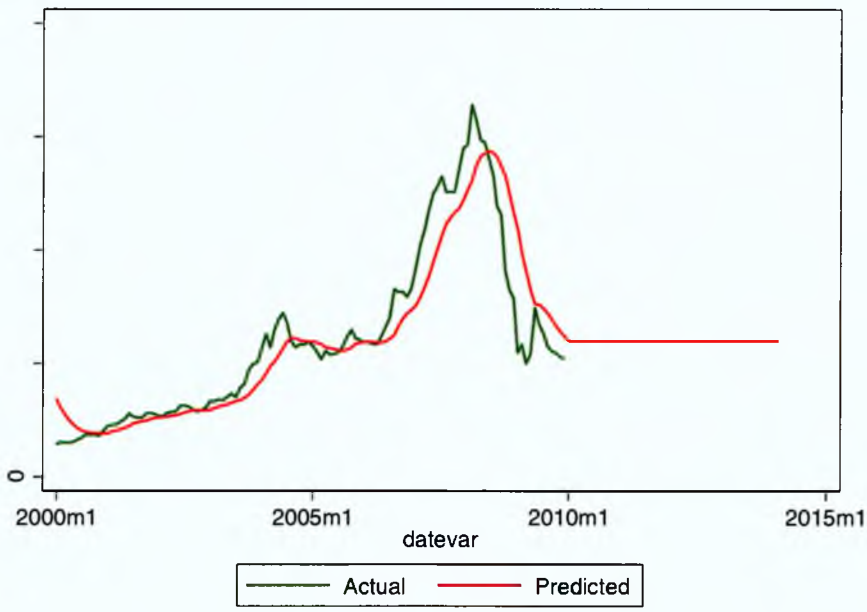
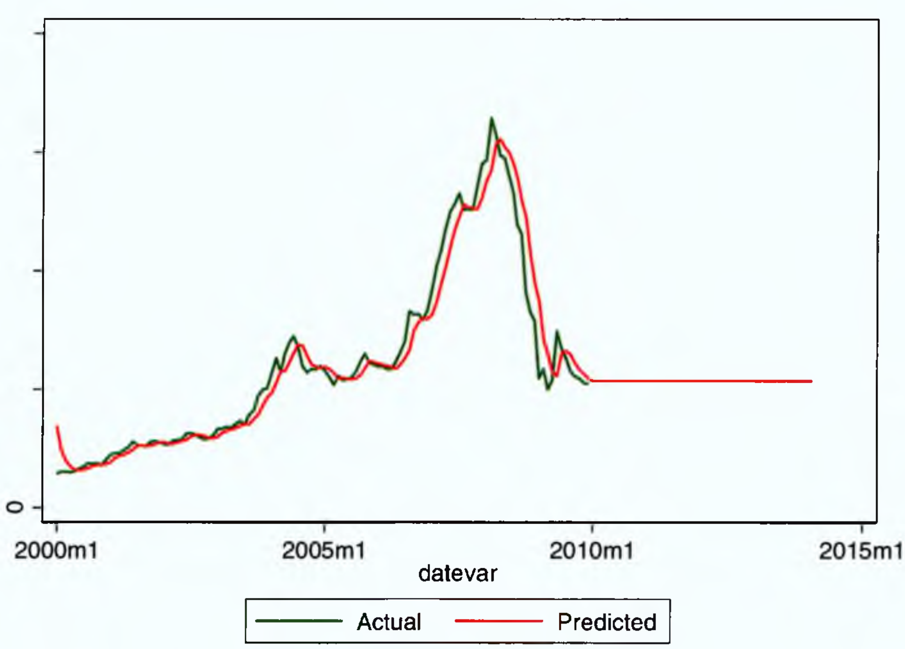
APPENDIXES

Appendix 5-1: Single exponential smoothing of the NSM Index, ω = 0.2000



tssmooth exponential MISES2 = MI, parms(0.2) forecast(50)
exponential coefficient = 0.2000
sum-of-squared residuals = 4144527489
root mean squared error = 5876.9

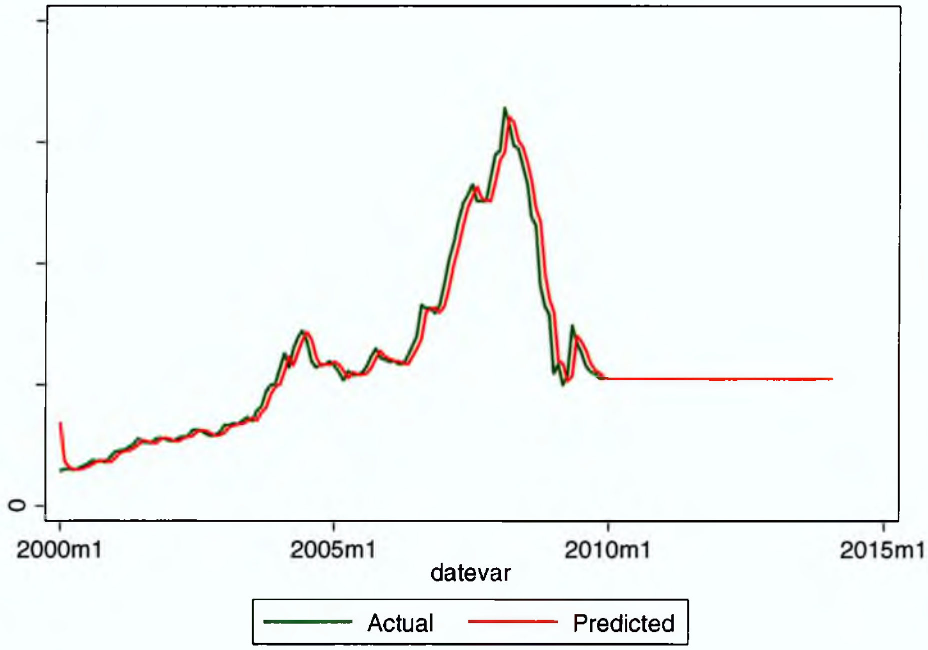
Appendix 5-2: Single exponential smoothing of the NSM Index, ω = 0.5000



tssmooth exponential MISES5 = MI, parms(0.5) forecast(50)

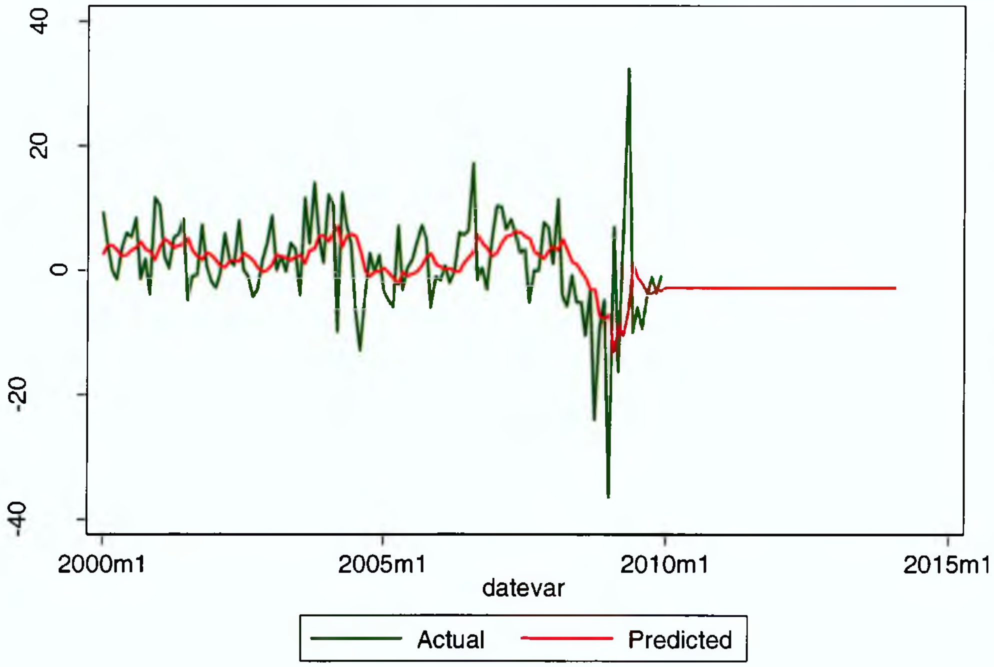
exponential coefficient = 0.5000
sum-of-squared residuals = 1367399244
root mean squared error = 3375.6

Appendix 5-3: Single exponential smoothing of the NSM Index, ω = 0.8000



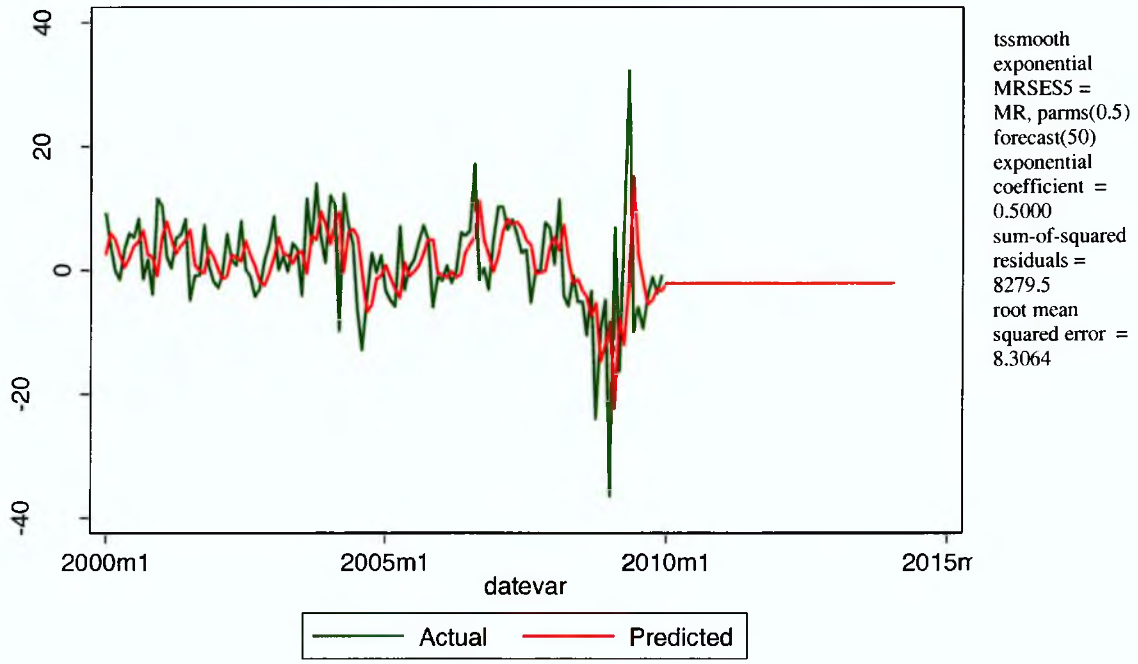
tssmooth exponential MISES8 = MI, parms(0.8) forecast(50)
exponential coefficient = 0.8000
sum-of-squared residuals = 828129899
root mean squared error = 2627

Appendix 5-4: Single exponential smoothing of the NSM Returns, ω = 0.2000

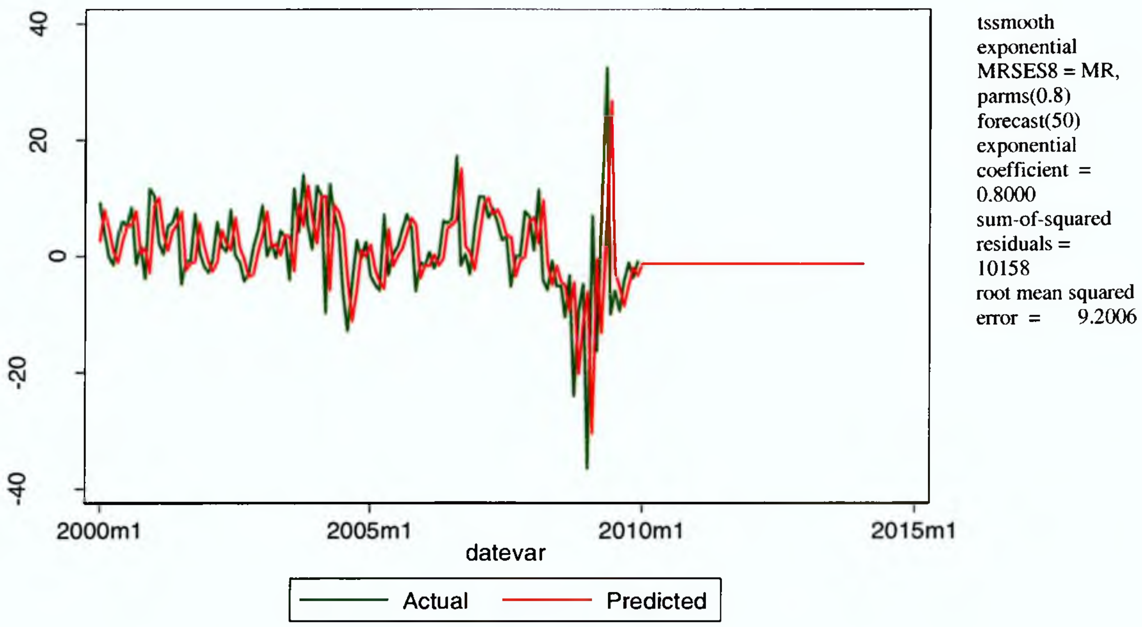


tssmooth exponential MRSES2 = MR, parms(0.2) forecast(50)
exponential coefficient = 0.2000
sum-of-squared residuals = 7258.6
root mean squared error = 7.7774

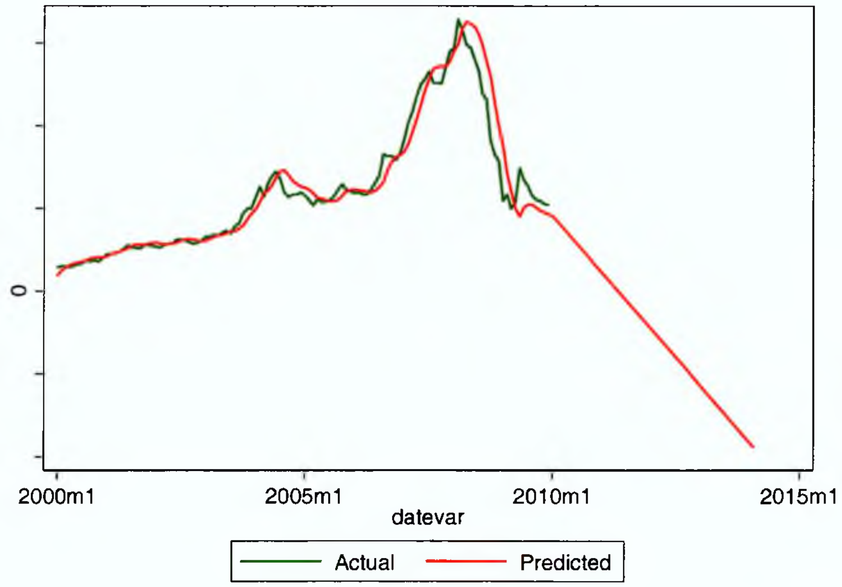
Appendix 5-5: Single exponential smoothing of the NSM Returns, ω = 0.5000



Appendix 5-6: Single exponential smoothing of the NSM Returns, ω = 0.8000

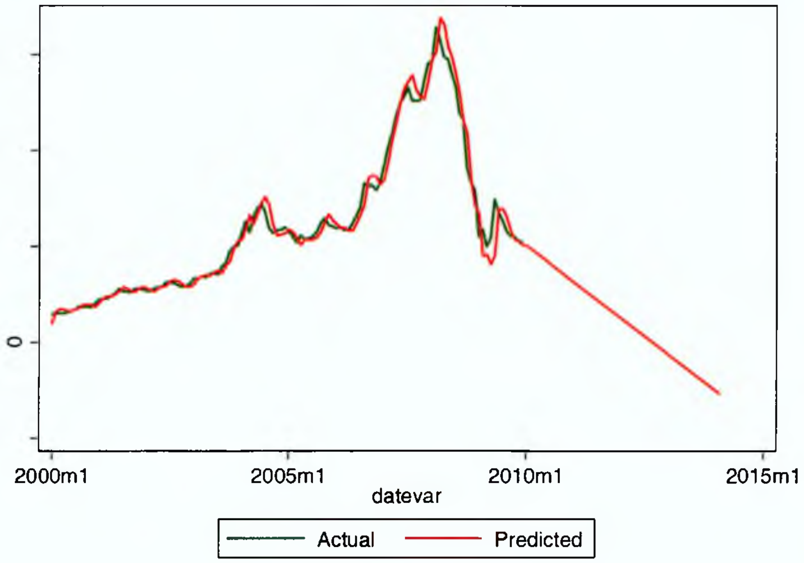


Appendix 5-7: Double exponential smoothing of the NSM Index, ω = 0.2000



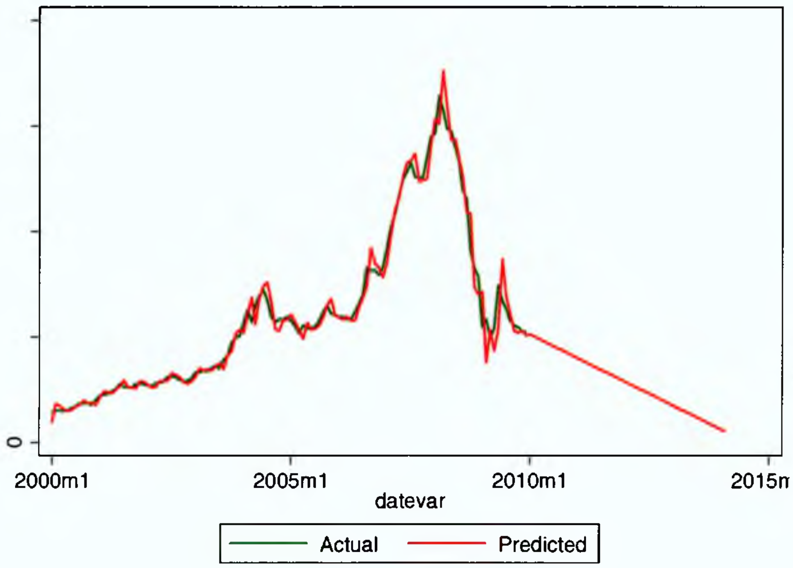
tssmooth dexponential MIDES2 = MI, parms(0.2) forecast(50)
double-exponential coefficient = 0.2000
sum-of-squared residuals = 1789834039
root mean squared error = 3862

Appendix 5-8: Double exponential smoothing of the NSM Index, ω = 0.5000



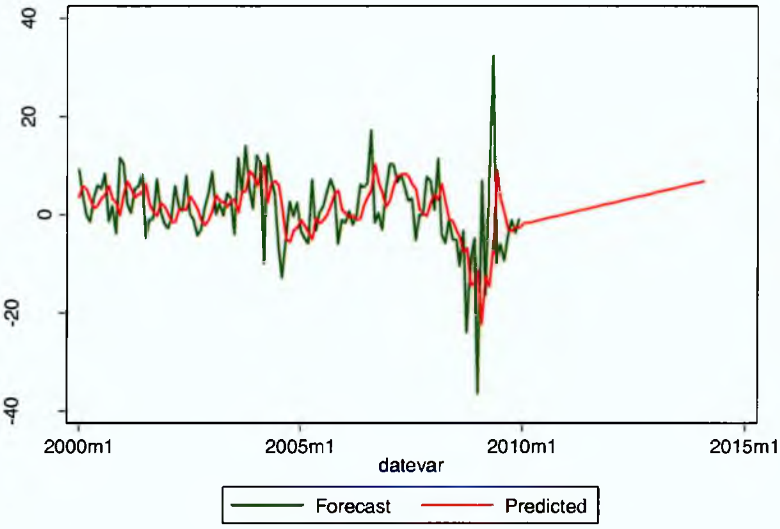
tssmooth dexponential MIDES5 = MI, parms(0.5) forecast(50)
double-exponential coefficient = 0.5000
sum-of-squared residuals = 664856698
root mean squared error = 2353.8

Appendix 5-9: Double exponential smoothing of the NSM Index, ω = 0.8000



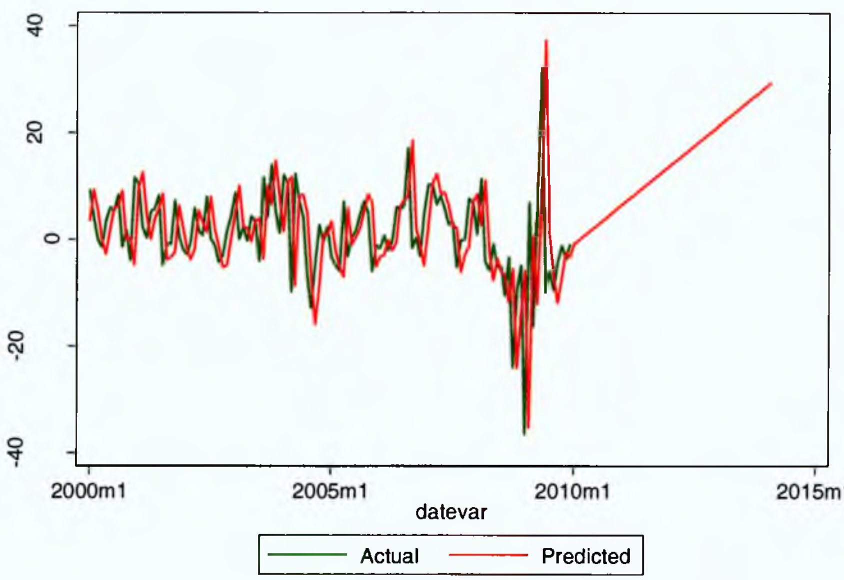
tssmooth dexponential MIDES8 = MI, parms(0.8) forecast(50) double-exponential coefficient = 0.8000 sum-of-squared residuals = 692647071 root mean squared error = 2402.5

Appendix 5-10: Double exponential smoothing of the NSM returns, ω = 0.2000



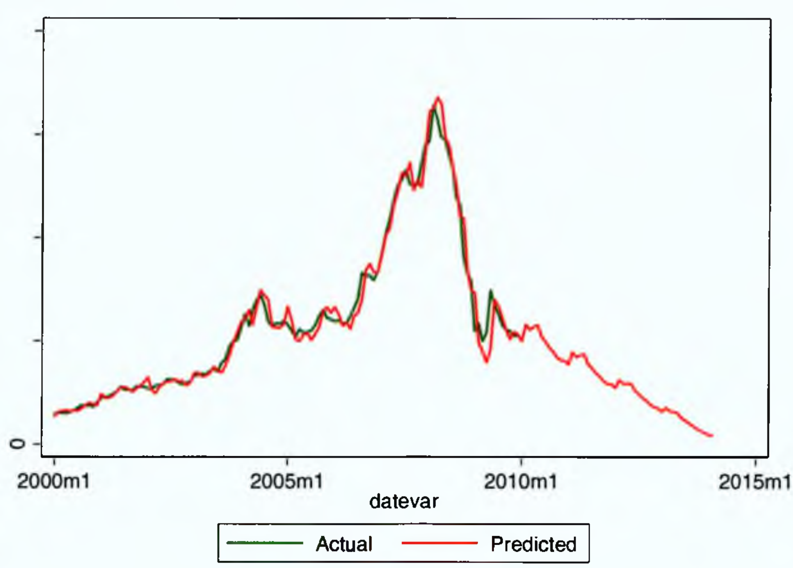
tssmooth dexponential MRDES2 = MR, parms(0.2) forecast(50) double-exponential coefficient = 0.2000 sum-of-squared residuals = 8266.2 root mean squared error = 8.2997

Appendix 5-11: Double exponential smoothing of the NSM returns, ω = 0.5000



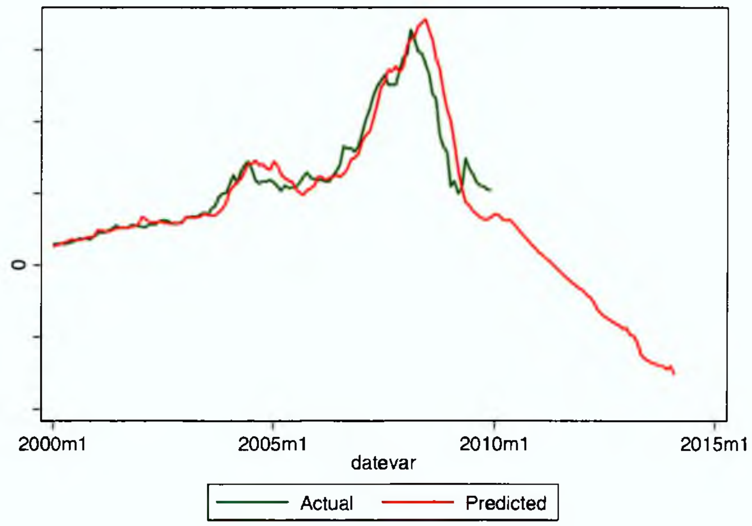
tssmooth dexponential MRDES5 = MR, parms(0.5) forecast(50)
double-exponential coefficient = 0.5000
sum-of-squared residuals = 12583
root mean squared error = 10.24

Appendix 5-12: Holt Winters model of the NSM Index, date 2000-2009, L = 0.8200, T=0.3202, S=1.0000



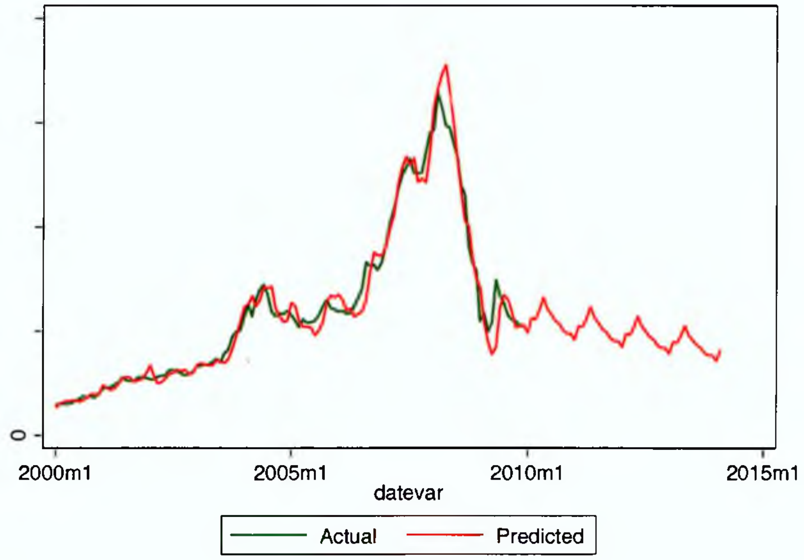
omega = 0.8200
beta = 0.3202
gamma = 1.0000
penalized sum-of-squared residuals = 6.27e+08
sum-of-squared residuals = 6.27e+08
root mean squared error = 2286.722

Appendix 5-13: Holt Winters model of the NSM Index, date 2000-2010, L = 0.2000, T=0.2000, S=0.2000



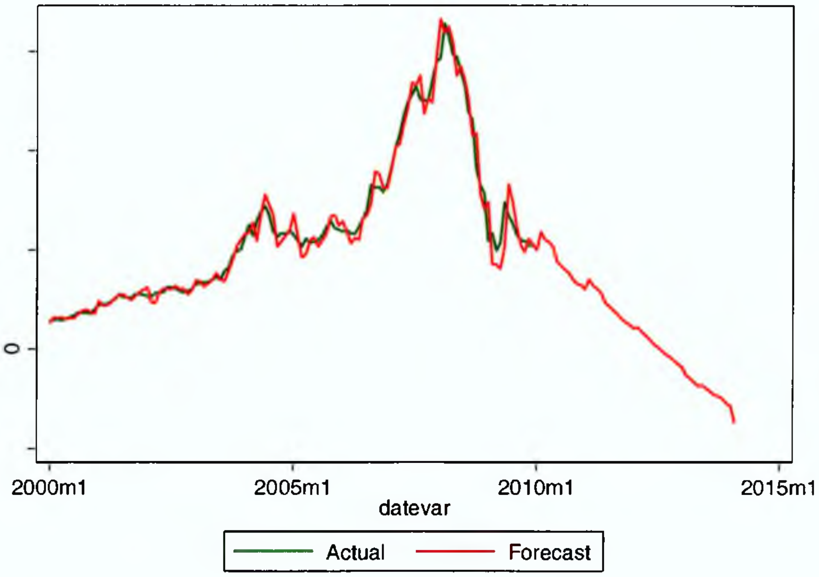
tssmooth
shwinters
MIHWN2 = MI,
parms(0.2 0.2 0.2)
forecast(50)
Specified weights:
omega = 0.2000
beta = 0.2000
gamma = 0.2000
sum-of-squared
residuals =
3.40e+09
root mean
squared error =
5319.272

Appendix 5-14: Holt Winters model of the NSM Index, date 2000-2009, L = 0.5000, T=0.5000, S=0.5000



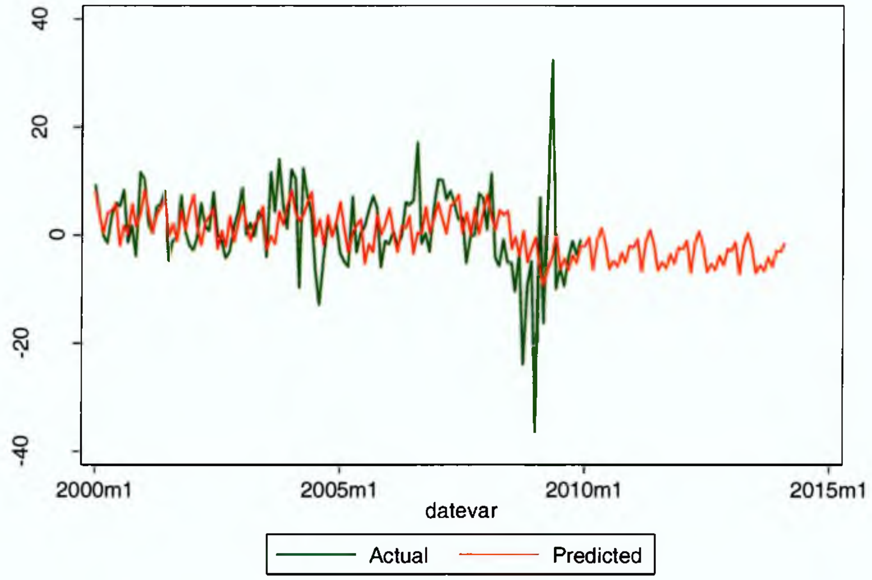
tssmooth shwinters
MIHWN5 = MI,
parms(0.5 0.5 0.5)
forecast(50)
Specified weights:
omega = 0.5000
beta = 0.5000
gamma = 0.5000
sum-of-squared
residuals = 8.97e+08
root mean squared
error = 2733.331

Appendix 5-15: Holt Winters model of the NSM Index, date 2000-2010, L = 0.8000, T=0.8000, S=0.8000



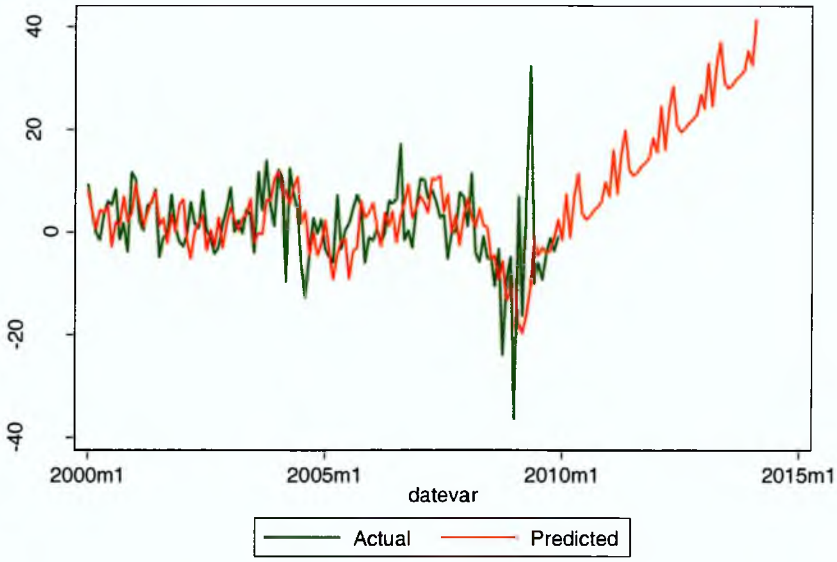
tssmooth shwinters MIHWN8 = MI, parms(0.8 0.8 0.8) forecast(50)
Specified weights:
omega = 0.8000
beta = 0.8000
gamma = 0.8000
sum-of-squared residuals = 7.16e+08
root mean squared error = 2443.264

Appendix 5-16: Holt Winters model of the NSM returns, date 2000-2010, L= 0.4999, T=0.5009, S=0.5012



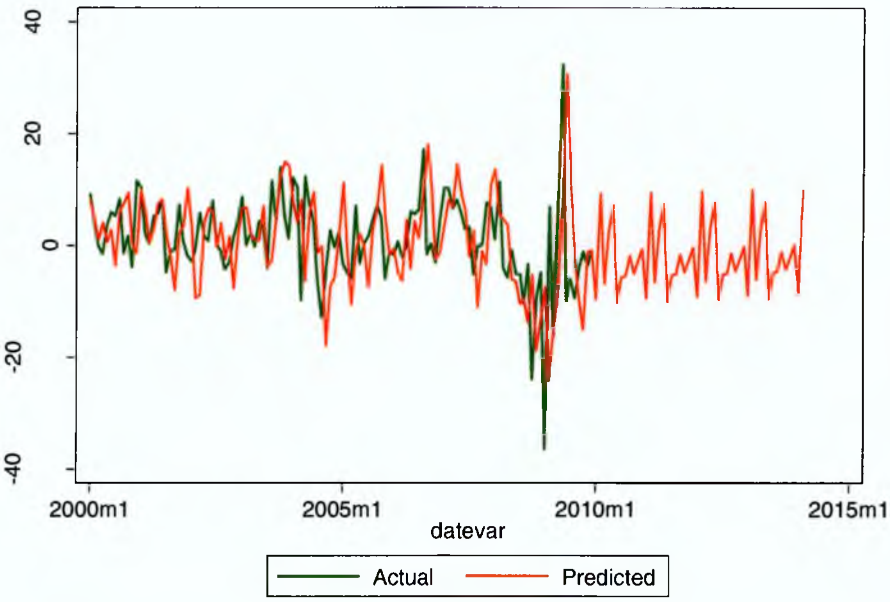
tssmooth shwinters MRHWN = MR, forecast(50)
Optimal weights:
alpha = 0.0990
beta = 0.0000
gamma = 0.0848
penalized sum-of-squared residuals = 7121.959

Appendix 5-17: Holt Winters model of the NSM returns, date 2000-2010, L= 0.2000, T=0.2000, S=0.2000



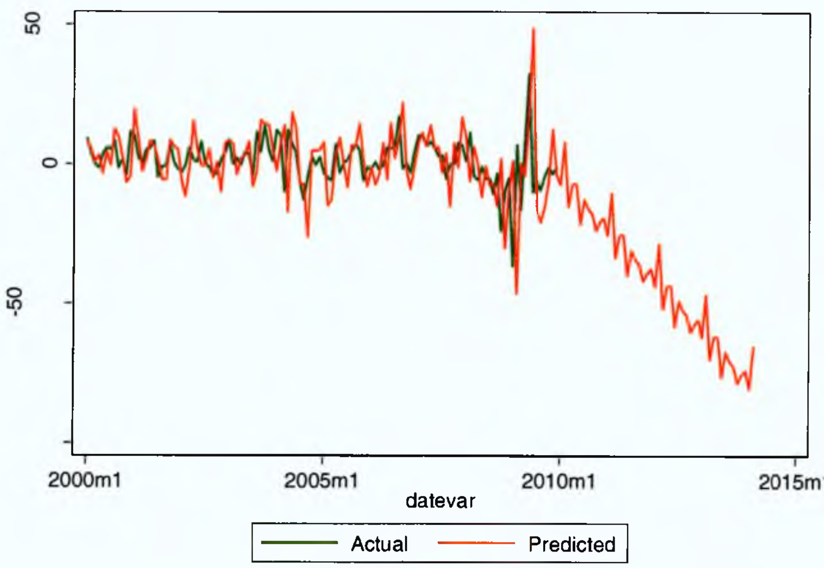
tssmooth shwinters MRHWN2 = MR, parms(0.2 0.2 0.2) forecast(50)
Specified weights:
alpha = 0.2000
beta = 0.2000
gamma = 0.2000
sum-of-squared residuals = 8116.272
root mean squared error = 8.224086

Appendix 5-18: Holt Winters model of the NSM returns, date 2000-2010, L= 0.5000, T=0.5000, S=0.5000



tssmooth shwinters MRHWN5 = MR, parms(0.5 0.5 0.5) forecast(50)
Specified weights:
alpha = 0.5000
beta = 0.5000
gamma = 0.5000
sum-of-squared residuals = 11034.13
root mean squared error = 9.589114

Appendix 5-19: Holt Winters model of the NSM returns, date 2000-2010, L= 0.8000, T=0.8000, S=0.8000



tssmooth shwinters MRHWN8 = MR, parms(0.8 0.8 0.8) forecast(50)
Specified weights:
alpha = 0.8000
beta = 0.8000
gamma = 0.8000
sum-of-squared residuals = 17952.39
root mean squared error = 12.23124

Appendix 6-1: BDS test result for daily return (2000-2010)

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.061611	0.001918	32.11497	0.0000
3	0.104567	0.003046	34.32803	0.0000
4	0.129755	0.003625	35.79627	0.0000
5	0.141398	0.003776	37.44816	0.0000
6	0.143172	0.003639	39.33953	0.0000
7	0.138941	0.003333	41.68119	0.0000
8	0.131848	0.002945	44.77223	0.0000

Raw epsilon	1.409750		
Pairs within epsilon	4723312.	V-Statistic	0.703035
Triples within epsilon	9.46E+09	V-Statistic	0.543084

Dimension	C(m,n)	c(m,n)	C(1,n-(m-1))	c(1,n-(m-1))	c(1,n-(m-1))^k
2	1866458.	0.556264	2359867.	0.703316	0.494653
3	1518613.	0.452945	2359131.	0.703640	0.348378
4	1255682.	0.374812	2357128.	0.703585	0.245057
5	1050070.	0.313681	2354935.	0.703474	0.172282
6	883983.0	0.264271	2352798.	0.703379	0.121098
7	750394.0	0.224507	2352505.	0.703836	0.085566
8	641240.0	0.191998	2350324.	0.703728	0.060150

Appendix 6-2: BDS test result for daily return (2000-2004)

BDS Test for RETURN
Date: 06/22/11 Time: 13:21
Sample: 1/03/2000 12/31/2004
Included observations: 1130

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.044576	0.002871	15.52471	0.0000
3	0.077508	0.004565	16.97945	0.0000
4	0.095337	0.005439	17.52878	0.0000
5	0.100530	0.005673	17.72237	0.0000
6	0.098021	0.005474	17.90570	0.0000
7	0.092329	0.005020	18.39133	0.0000
8	0.086064	0.004440	19.38176	0.0000

Raw epsilon	1.300125		
Pairs within epsilon	898750.0	V-Statistic	0.703853
Triples within epsilon	7.84E+08	V-Statistic	0.543648

Dimension	C(m,n)	c(m,n)	C(1,n-(m-1))	c(1,n-(m-1))	c(1,n-(m-1))^k
2	344504.0	0.541030	448655.0	0.704595	0.496454
3	271483.0	0.427110	447776.0	0.704462	0.349602
4	216782.0	0.341657	447000.0	0.704491	0.246321
5	173404.0	0.273778	446061.0	0.704261	0.173247
6	138986.0	0.219828	445144.0	0.704063	0.121806
7	112272.0	0.177892	444207.0	0.703833	0.085563
8	92102.00	0.146193	443331.0	0.703697	0.060129

Appendix 6-3: BDS test result for daily return (2005-2010)

BDS Test for RETURN
Date: 06/22/11 Time: 13:22
Sample: 1 1462
Included observations: 1462

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.070876	0.002531	28.00463	0.0000
3	0.119717	0.004024	29.75228	0.0000
4	0.149863	0.004794	31.25753	0.0000
5	0.166495	0.005001	33.29448	0.0000
6	0.172047	0.004826	35.64875	0.0000
7	0.169813	0.004426	38.36636	0.0000
8	0.163483	0.003915	41.75671	0.0000

Raw epsilon	1.494210		
Pairs within epsilon	1504628.	V-Statistic	0.703938
Triples within epsilon	1.70E+09	V-Statistic	0.543897

Dimension	C(m,n)	c(m,n)	C(1,n-(m-1))	c(1,n-(m-1))	c(1,n-(m-1))^k
2	604734.0	0.567011	751230.0	0.704368	0.496135
3	500592.0	0.470009	750795.0	0.704925	0.350292
4	421853.0	0.396623	749638.0	0.704805	0.246760
5	361323.0	0.340180	748410.0	0.704616	0.173685
6	312109.0	0.294249	747201.0	0.704444	0.122202
7	271787.0	0.256587	747026.0	0.705247	0.086774
8	237529.0	0.224553	745806.0	0.705064	0.061070

Appendix 6-4: BDS test result for monthly return (2000-2010)

BDS Test for RETURN
Date: 06/22/11 Time: 13:23
Sample: 2000M01 2010M12
Included observations: 132

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.025055	0.006862	3.651009	0.0003
3	0.053288	0.010954	4.864739	0.0000
4	0.065116	0.013100	4.970531	0.0000
5	0.065040	0.013713	4.742957	0.0000
6	0.061637	0.013281	4.640855	0.0000
7	0.060695	0.012223	4.965741	0.0000
8	0.056829	0.010849	5.238139	0.0000

Raw epsilon	9.613122		
Pairs within epsilon	12294.00	V-Statistic	0.705579
Triples within epsilon	1235342.	V-Statistic	0.537113

Dimension	C(m,n)	c(m,n)	C(1,n-(m-1))	c(1,n-(m-1))	c(1,n-(m-1))^k
2	4399.000	0.516618	5970.000	0.701116	0.491563
3	3306.000	0.394275	5858.000	0.698629	0.340988
4	2510.000	0.304021	5772.000	0.699128	0.238906
5	1894.000	0.233022	5689.000	0.699926	0.167981
6	1450.000	0.181227	5616.000	0.701912	0.119591
7	1122.000	0.142476	5507.000	0.699302	0.081781
8	880.0000	0.113548	5414.000	0.698581	0.056719

Appendix 6-5: BDS test result for monthly return (2000-2004)

BDS Test for RETURN
Date: 06/22/11 Time: 13:24
Sample: 2000M01 2004M12
Included observations: 60

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.029556	0.008822	3.350159	0.0008
3	0.030963	0.014166	2.185661	0.0288
4	0.038704	0.017043	2.271044	0.0231
5	0.025946	0.017946	1.445786	0.1482
6	0.006603	0.017486	0.377643	0.7057
7	0.000501	0.016191	0.030959	0.9753
8	0.008704	0.014460	0.601922	0.5472

Raw epsilon	8.173343		
Pairs within epsilon	2546.000	V-Statistic	0.707222
Triples within epsilon	115354.0	V-Statistic	0.534046

Dimension	C(m,n)	c(m,n)	C(1,n-(m-1))	c(1,n-(m-1))	c(1,n-(m-1))^k
2	881.0000	0.514904	1192.000	0.696669	0.485347
3	602.0000	0.364186	1146.000	0.693285	0.333223
4	418.0000	0.261905	1097.000	0.687343	0.223200
5	287.0000	0.186364	1068.000	0.693506	0.160418
6	213.0000	0.143434	1066.000	0.717845	0.136831
7	155.0000	0.108316	1041.000	0.727463	0.107815
8	113.0000	0.082003	994.0000	0.721335	0.073299

Appendix 6-6: BDS test result for monthly return (2005-2010)

BDS Test for RETURN
Date: 06/22/11 Time: 13:25
Sample: 2005M01 2010M12
Included observations: 72

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.018852	0.010701	1.761674	0.0781
3	0.054985	0.017232	3.190827	0.0014
4	0.072418	0.020795	3.482379	0.0005
5	0.077337	0.021969	3.520346	0.0004
6	0.075797	0.021476	3.529393	0.0004
7	0.075502	0.019952	3.784254	0.0002
8	0.071078	0.017879	3.975488	0.0001

Raw epsilon	10.89725		
Pairs within epsilon	3674.000	V-Statistic	0.708719
Triples within epsilon	204304.0	V-Statistic	0.547368

Dimension	C(m,n)	c(m,n)	C(1,n-(m-1))	c(1,n-(m-1))	c(1,n-(m-1))^k
2	1261.000	0.507445	1737.000	0.698994	0.488593
3	940.0000	0.389234	1676.000	0.693996	0.334249
4	722.0000	0.307758	1634.000	0.696505	0.235340
5	550.0000	0.241440	1587.000	0.696664	0.164103
6	424.0000	0.191768	1544.000	0.698327	0.115972
7	327.0000	0.152448	1487.000	0.693240	0.076946
8	254.0000	0.122115	1434.000	0.689423	0.051037

Appendix 7-1: The calculation of $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ and ε_t (abnormal returns (Residuals)) and the Monthly positive and negative abnormal returns for the period 2000-2010.

	Coefficients	*Standard Error*	*t Stat*	*P-value*
α_0	0.689425	0.682377	1.010329	0.31429
α_1	0.124122	0.088891	1.396339	0.165087
α_2	0.12999	0.088871	1.462687	0.146063
α_3	0.10838	0.088769	1.220926	0.224412

RESIDUAL OUTPUT					
Observation	*Predicted Y*	*Residuals*		Positive	Negative
1	2.335967	-4.10278		4	1
2	0.925608	2.454706		3	3
3	0.897322	5.015837		3	1
4	1.671299	4.824394		1	3
5	2.630696	4.275255		2	4
6	3.031852	-4.32773		1	1
7	2.130291	-0.54811		4	4
8	1.465826	-5.28551		2	2
9	0.280539	12.50672		4	1
10	1.95156	6.135568		2	1
11	2.941457	0.820104		3	1
12	3.593453	-3.28183		3	3
13	2.093557	2.51174		1	3
14	1.709231	3.98784		4	2
15	2.028975	5.40412		1	3
16	2.851723	-6.2071		4	2
17	1.85663	-3.61456		6	3
18	0.840662	-1.98166		1	1
19	-0.04437	7.697783		2	3
20	1.300539	-0.59797		1	1
21	1.647839	-3.51391		1	11
22	1.378611	-4.27613		2	1
23	0.163354	-0.80484		1	4
24	0.030909	5.774458		3	2
25	1.012578	0.620115		1	3
26	1.577196	-0.81077		1	2
27	1.625977	6.351566			2
28	1.956193	-1.81482			
29	1.827042	-2.87845			

30	1.441909	-5.72105			
31	0.036941	-3.13223			
32	-0.36497	1.848903			
33	0.007483	4.32814			
34	1.085	7.592515			
35	2.490914	0.711523			
36	2.684807	-3.69732			
37	1.920507	-2.23954			
38	0.865291	3.47423			
39	1.076848	2.269163			
40	1.634258	-5.76854			
41	1.081538	10.55324			
42	1.958782	2.272705			
43	2.27898	11.68718			
44	4.233965	1.139019			
45	3.630406	-2.52001			
46	3.039342	9.059698			
47	2.917848	7.498108			
48	3.675378	-13.5597			
49	2.127839	10.20466			
50	2.064181	5.179879			
51	2.120417	1.965796			
52	3.474872	-10.0019			
53	1.195557	-14.1487			
54	-1.32393	-3.12532			
55	-2.25401	4.923127			
56	-0.9615	0.599893			
57	0.50929	1.927421			
58	1.234149	-4.57956			
59	0.551745	-5.46904			
60	-0.0917	-5.87265			
61	-1.05266	8.151591			
62	0.262314	-3.56756			
63	0.555548	-0.17131			
64	1.076852	0.515788			
65	0.578831	3.990448			
66	1.505245	5.647071			
67	2.343758	2.558858			
68	2.722899	-8.76898			
69	1.351436	-2.46619			
70	0.296474	-1.99817			
71	-0.32198	1.010495			
72	0.432864	-2.57964			
73	0.328034	-0.47984			
74	0.466144	5.548543			
75	1.183578	4.378988			

76	2.14526	4.219755			
77	2.854417	14.29528			
78	4.248341	-5.89892			
79	3.403689	-3.13037			
80	2.367479	-5.51416			
81	0.155492	4.648756			
82	0.906323	9.378577			
83	2.249475	7.941078			
84	3.81192	2.664998			
85	3.932706	4.170409			
86	3.641591	2.142768			
87	3.162688	-0.39678			
88	2.662864	0.578749			
89	2.078233	-7.36554			
90	0.754303	-0.87786			
91	0.338117	-0.39228			
92	0.093601	7.550761			
93	1.617826	5.160124			
94	2.51854	-1.52265			
95	2.522603	8.891521			
96	2.97022	-7.06781			
97	1.772485	-7.61405			
98	0.668777	-1.5337			
99	-0.62138	-4.5679			
100	-0.70022	-4.50562			
101	-0.72503	-9.83322			
102	-1.86021	-1.48693			
103	-1.66271	-22.417			
104	-3.8788	-5.64539			
105	-3.98563	-0.90083			
106	-3.76491	-32.8232			
107	-5.51939	12.4408			
108	-3.73718	-12.6085			
109	-4.40515	12.33907			
110	0.299557	32.1068			
111	3.971544	-14.0724			
112	4.508082	-10.55			
113	2.138685	-11.5772			
114	-2.36222	-1.82749			
115	-1.71235	0.525635			
116	-1.02544	-2.68583			
117	-0.37957	-0.49574			
118	-0.03026	8.176709			
119	1.184569	0.527191			
120	1.865986	10.89852			
121	3.379207	-2.09019			

122	2.694205	-3.72012			
123	2.113068	-5.21257			
124	0.311055	1.586979			
125	0.41092	-6.80457			
126	-0.19336	-4.95414			
127	-0.5749	8.861798			
128	0.355941	-1.4703			
129	1.070439	-1.04674			

Sours: Calculated using Excel 2007

Appendix 7-2: The calculation of $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ and ε_t (abnormal returns (Residuals)) and the Weekly positive and negative abnormal returns for the period 2000-2010.

	Coefficients	*Standard Error*	*t Stat*	*P-value*
α_0	0.212914	0.137091	1.553091	0.120963
α_1	0.065374	0.042074	1.553774	0.1208
α_2	0.048244	0.042142	1.144786	0.252784
α_3	0.062794	0.042092	1.491841	0.136301

RESIDUAL OUTPUT					
				Positive	Negative
Observation	*Predicted Y*	*Residuals*		3	2
1	0.632527	2.585898		1	1
2	0.712322	2.876204		1	3
3	0.872124	3.76855		1	1
4	0.891515	-5.30516		2	1
5	0.373597	-0.70466		2	1
6	0.269748	0.422199		4	1
7	-0.03497	-2.18936		2	2
8	0.080094	0.674881		2	1
9	0.19841	1.436973		1	3
10	0.216574	-1.95369		3	3
11	0.225656	-0.14069		1	1
12	0.237356	-0.85217		6	4
13	0.067739	0.432422		1	1
14	0.221286	-0.04834		2	2
15	0.209743	0.726064		2	1
16	0.313842	2.459134		1	1
17	0.450201	-0.85225		1	1
18	0.379172	0.419729		2	2
19	0.419872	0.529047		3	2
20	0.288245	-0.26763		1	3
21	0.310207	2.153905		2	3
22	0.434584	1.146662		3	4
23	0.436458	0.67537		3	2
24	0.516615	5.416406		1	1
25	0.753711	-3.05712		1	1
26	0.418377	0.096466		1	4
27	0.508005	6.040983		3	1
28	0.521245	-3.57411		1	3
29	0.361612	-0.00522		1	2
30	0.500169	2.897425		2	1
31	0.260521	1.322903		3	1

32	0.50272	-2.42925		1	1
33	0.376708	1.165473		1	1
34	0.32022	-0.25943		2	2
35	0.170314	-1.83081		1	4
36	0.204133	-1.43515		1	3
37	0.056147	0.549536		2	1
38	0.088852	0.304672		2	1
39	0.19056	1.184179		1	1
40	0.359805	-1.39866		4	1
41	0.236033	-1.65716		3	2
42	0.156217	-1.18742		1	2
43	0.011706	0.817999		1	1
44	0.128168	-1.01259		1	2
45	0.130371	1.394654		2	1
46	0.322044	1.954509		6	5
47	0.379778	4.348772		4	3
48	0.72763	3.694963		5	1
49	0.873113	1.254268		3	2
50	0.862276	7.540602		1	1
51	1.142589	-0.63896		8	1
52	0.78481	-3.61679		1	1
53	0.579724	-0.94613		1	1
54	0.083961	-0.59941		4	3
55	-0.01629	3.373975		2	1
56	0.384544	-0.21073		3	5
57	0.353896	3.487013		2	2
58	0.683238	0.290214		1	4
59	0.472766	-2.10728		2	1
60	0.394208	-2.41714		4	4
61	0.062939	0.08892		1	1
62	0.02261	1.979101		1	2
63	0.224072	-0.48229		1	2
64	0.302139	1.759935		1	3
65	0.460958	-0.85057		1	3
66	0.270711	2.336878		3	5
67	0.494072	-4.77369		3	3
68	0.034472	6.603206		1	1
69	0.604123	0.689301		2	1
70	0.348961	-0.00565		3	1
71	0.714563	-0.58132		3	1
72	0.319407	0.337305		2	1
73	0.283832	3.498588		1	4
74	0.500235	2.644522		1	1
75	0.642215	-2.58558		2	5
76	0.475096	-3.11622		2	8
77	0.14397	2.558669		1	1

78	0.140147	-2.27297		4	1
79	0.038021	-0.35069		1	1
80	0.259288	-2.54312		5	1
81	-0.0854	0.474388		3	1
82	0.10853	1.560749		3	2
83	0.197397	-0.75779		2	2
84	0.281237	-1.18309		1	3
85	0.231742	-0.76526		4	1
86	0.099338	0.195037		7	2
87	0.149789	1.514272		7	1
88	0.3024	6.445918		1	1
89	0.752844	-0.81371		5	1
90	0.638991	-0.51461		2	2
91	0.641863	-1.45442		2	3
92	0.161972	-0.9721		2	3
93	0.128563	0.269629		2	3
94	0.148839	0.659868		3	1
95	0.234122	0.06176		1	1
96	0.296276	-2.88188		3	3
97	0.10894	-0.86238		6	4
98	0.0575	0.814393		1	3
99	0.071204	-0.02167		1	4
100	0.210904	0.122403		1	1
101	0.291843	-0.52431		2	3
102	0.216907	0.754191		1	3
103	0.286113	-2.62443		2	9
104	0.092301	-1.22073		1	4
105	0.087314	-1.73065		3	4
106	-0.09579	-2.54396		1	2
107	-0.1098	0.470965		1	4
108	0.005983	5.331907		1	1
109	0.413537	5.266485		1	1
110	0.864438	-2.99413		4	1
111	0.6829	1.733416		1	2
112	0.624806	-2.7947		1	2
113	0.053899	-0.77702		3	2
114	0.212688	-0.65828		1	2
115	0.012642	4.928181		4	1
116	0.469011	-1.64806		1	3
117	0.346217	-1.12778		1	1
118	0.415193	0.980524		1	1
119	0.192415	0.472038		1	1
120	0.274609	-2.5171		3	1
121	0.186012	0.583924		2	1
122	0.196786	1.973337		1	2
123	0.251113	5.795564		6	2

124	0.761252	-3.86165		2	4
125	0.438213	2.422929		1	1
126	0.630079	-0.61962		1	1
127	0.156943	2.050481		3	2
128	0.537389	-3.1596		1	1
129	0.148641	2.242164		1	3
130	0.381319	2.069065		3	3
131	0.323788	-2.50896		1	1
132	0.338404	-1.62455		1	2
133	0.177282	1.281622		1	1
134	0.109024	-3.44349			
135	-0.01545	-1.04713			
136	0.074193	-1.79248			
137	-0.16006	-0.33575			
138	0.030881	0.553306			
139	0.119287	-0.51088			
140	0.184364	-0.6447			
141	0.200612	-4.53224			
142	-0.11706	0.870739			
143	0.024306	0.600021			
144	0.018089	-0.84296			
145	0.236436	0.448101			
146	0.257075	0.490814			
147	0.243034	-0.38252			
148	0.282861	0.040568			
149	0.274292	-0.95592			
150	0.175198	2.206082			
151	0.356013	2.721845			
152	0.486205	3.273908			
153	0.756745	4.289632			
154	0.917488	-2.41306			
155	0.59471	0.146055			
156	0.506071	2.943337			
157	0.38024	3.60284			
158	0.686231	-1.60209			
159	0.561801	-3.87599			
160	0.202182	0.296251			
161	0.0281	-0.55872			
162	-0.00584	-0.98631			
163	0.153753	0.404939			
164	0.168254	-0.7373			
165	0.140366	0.397068			
166	0.255678	-0.87076			
167	0.162899	-1.84893			
168	0.106766	1.27624			
169	0.183363	0.937458			

170	0.247035	-0.35789			
171	0.346584	1.754806			
172	0.415323	0.896653			
173	0.393101	0.079296			
174	0.439046	0.994847			
175	0.411828	0.376986			
176	0.363322	0.034615			
177	0.367024	-0.25902			
178	0.288706	-0.07511			
179	0.257077	-1.3477			
180	0.158703	-2.20412			
181	0.039994	-1.20423			
182	-0.03036	2.265608			
183	0.174435	2.605661			
184	0.42939	4.595458			
185	0.815891	0.876052			
186	0.740513	-0.50067			
187	0.625749	-0.17751			
188	0.360032	-0.32335			
189	0.251997	1.642776			
190	0.366699	2.727026			
191	0.508877	5.407728			
192	0.867939	4.344702			
193	1.033391	0.481447			
194	0.934949	-1.09464			
195	0.602878	4.968669			
196	0.664567	0.901507			
197	0.574058	3.150175			
198	0.881795	-6.37067			
199	0.132095	-7.35824			
200	-0.29043	8.419247			
201	0.051044	-4.42752			
202	-0.13479	2.148798			
203	0.643882	2.094874			
204	0.214304	3.317419			
205	0.702392	2.721824			
206	0.779129	2.965637			
207	0.844692	0.385084			
208	0.688991	0.062602			
209	0.556527	8.375702			
210	0.910332	-3.4165			
211	0.527194	2.711112			
212	0.864599	-8.77468			
213	-0.30534	1.963424			
214	0.143045	-3.18542			
215	-0.40269	0.536454			

216	0.179001	1.179403			
217	0.117129	6.428875			
218	0.714786	4.184345			
219	0.934292	-0.86842			
220	0.864622	-2.1252			
221	0.441319	-0.49173			
222	0.15294	5.723344			
223	0.515481	0.087296			
224	0.532647	-1.3467			
225	0.557772	1.458231			
226	0.343287	3.04292			
227	0.480426	5.930118			
228	0.921953	-8.06546			
229	0.267815	-2.16607			
230	0.146733	-1.46487			
231	-0.41341	-1.06137			
232	-0.06629	-1.66476			
233	-0.05417	0.995771			
234	0.098351	0.419697			
235	0.183507	-2.44878			
236	0.148943	-13.2014			
237	-0.71713	6.769859			
238	-0.16334	-5.31497			
239	-0.67284	-0.81791			
240	0.23124	-2.0311			
241	-0.32067	-0.2422			
242	-0.00432	0.680711			
243	0.116957	0.349943			
244	0.240724	-0.1869			
245	0.281431	1.236835			
246	0.344085	0.286038			
247	0.330734	1.743532			
248	0.474255	1.648636			
249	0.491334	-2.95073			
250	0.284801	-0.52241			
251	0.212036	-2.76634			
252	-0.11997	-1.59479			
253	-0.03734	1.519017			
254	0.066657	-0.3381			
255	0.158974	3.474795			
256	0.530413	-0.57446			
257	0.368296	-1.22874			
258	0.382717	0.010501			
259	0.194344	-3.02848			
260	-0.00743	-2.77775			
261	-0.0812	2.710575			

262	0.072473	-1.21561			
263	0.09014	-3.19146			
264	0.120129	-4.32329			
265	-0.28326	1.554981			
266	-0.10147	-1.8598			
267	-0.11788	-1.20667			
268	0.111561	-0.23846			
269	0.017561	1.310556			
270	0.210443	0.861101			
271	0.33907	4.972283			
272	0.695231	-1.44453			
273	0.487454	-1.39364			
274	0.451045	-1.31232			
275	0.06584	-0.96651			
276	0.055579	-1.10878			
277	0.046528	0.238672			
278	0.124192	0.654907			
279	0.211472	1.084336			
280	0.353122	-0.68421			
281	0.302707	-1.24616			
282	0.216633	-0.99277			
283	0.095869	0.584502			
284	0.160706	-0.55025			
285	0.171535	1.621175			
286	0.354041	0.441021			
287	0.326916	-1.92525			
288	0.259353	0.876536			
289	0.259987	0.855043			
290	0.240241	7.676206			
291	0.855564	-2.93549			
292	0.528876	1.265546			
293	0.726985	1.324078			
294	0.302963	0.288983			
295	0.463242	-0.59078			
296	0.361929	0.785321			
297	0.318932	4.900379			
298	0.60146	-2.10149			
299	0.43869	0.736274			
300	0.545101	-2.26818			
301	0.062761	-0.1913			
302	0.195165	-1.94201			
303	-0.01568	-4.55596			
304	-0.1783	1.425144			
305	-0.03582	-2.6887			
306	-0.19212	0.219503			
307	0.161558	1.286658			

308	0.137827	-0.05483			
309	0.289927	-0.14277			
310	0.317478	-1.68001			
311	0.136152	-0.06689			
312	0.16095	-0.91026			
313	0.081712	1.180311			
314	0.263618	0.318731			
315	0.264817	-0.84717			
316	0.282186	-0.74959			
317	0.190831	-1.46475			
318	0.070516	-0.64266			
319	0.084702	-0.0847			
320	0.105317	-0.40141			
321	0.15763	-0.14649			
322	0.199358	-0.70493			
323	0.161807	0.074762			
324	0.204688	-0.09863			
325	0.199513	2.583152			
326	0.4148	0.920647			
327	0.441123	0.212803			
328	0.494825	0.250346			
329	0.377035	-0.41969			
330	0.287138	0.900703			
331	0.335303	-0.95836			
332	0.22681	3.410597			
333	0.495237	1.405268			
334	0.473515	1.572595			
335	0.666771	0.958772			
336	0.537234	0.69576			
337	0.500425	-1.23503			
338	0.326449	5.524609			
339	0.637406	8.61133			
340	1.053688	8.97992			
341	1.682455	-14.2565			
342	0.455721	4.008968			
343	0.528222	1.867613			
344	-0.20464	0.845968			
345	0.65078	-1.01744			
346	0.370328	-2.37079			
347	0.104719	0.227708			
348	0.115113	2.431554			
349	0.269821	-2.22461			
350	0.228857	-0.85411			
351	0.237648	2.405356			
352	0.232784	-0.65873			
353	0.273314	-2.78144			

354	0.194364	-3.95142			
355	-0.18045	1.056161			
356	-0.06859	2.127694			
357	0.153853	1.344287			
358	0.465182	1.182347			
359	0.522195	-0.92272			
360	0.360287	0.874028			
361	0.377738	1.890294			
362	0.395582	3.060209			
363	0.625759	0.256773			
364	0.579747	6.324684			
365	0.923864	0.896582			
366	0.720436	4.466552			
367	1.07339	-2.44282			
368	0.487941	-1.37879			
369	0.414322	1.480724			
370	0.207831	0.243897			
371	0.27793	1.408437			
372	0.463949	2.963023			
373	0.546671	2.148846			
374	0.660354	2.137519			
375	0.741057	1.803501			
376	0.683504	-0.61812			
377	0.515637	0.115585			
378	0.417117	-1.18531			
379	0.197253	0.269778			
380	0.246023	1.947188			
381	0.330587	4.605729			
382	0.670756	0.443082			
383	0.661596	0.037516			
384	0.622325	-3.08536			
385	0.155566	1.584977			
386	0.251775	0.019822			
387	0.159976	-0.07453			
388	0.340899	-1.17776			
389	0.179383	1.392234			
390	0.28065	3.238239			
391	0.466229	-0.34334			
392	0.4894	-3.18336			
393	0.263693	-4.34106			
394	-0.17589	0.167936			
395	-0.15348	4.361461			
396	0.231589	-0.59141			
397	0.3919	-2.94527			
398	0.292867	-1.71122			
399	-0.02559	1.382481			

400	0.072857	0.521851			
401	0.22819	-0.03704			
402	0.339306	-1.48011			
403	0.184901	-0.68265			
404	0.137342	2.044776			
405	0.259919	2.972558			
406	0.498252	3.048061			
407	0.737721	-2.61264			
408	0.46441	0.272856			
409	0.393347	-0.64021			
410	0.11461	0.293142			
411	0.273957	3.643622			
412	0.473192	2.961826			
413	0.652077	-1.88289			
414	0.544169	-0.40492			
415	0.378337	-1.00941			
416	0.101089	2.087747			
417	0.334306	5.241707			
418	0.64341	1.051461			
419	0.730167	0.121745			
420	0.700514	1.6477			
421	0.513953	0.198632			
422	0.42628	-2.12909			
423	0.283426	-1.8634			
424	0.072221	-1.3929			
425	-0.05657	-1.41444			
426	-0.04618	2.445772			
427	0.215888	-3.91908			
428	-0.00578	-1.66773			
429	0.075535	-2.20873			
430	-0.23982	5.820217			
431	0.369728	-0.53462			
432	0.337401	-3.33766			
433	0.359236	-3.10637			
434	-0.12177	-4.5594			
435	-0.41404	7.215502			
436	0.259212	-10.4091			
437	-0.41645	1.37393			
438	0.212931	0.785978			
439	-0.31295	-1.13007			
440	0.226894	-4.66937			
441	-0.0844	-3.54584			
442	-0.32934	4.635667			
443	0.040339	-5.78327			
444	-0.18273	-4.31437			
445	-0.08773	-6.79586			

446	-0.81467	8.267584			
447	0.085661	3.664907			
448	0.38541	-2.16983			
449	0.745198	-3.70245			
450	0.169013	-2.52505			
451	-0.19583	-0.90004			
452	-0.15809	-2.79772			
453	-0.18113	-3.07912			
454	-0.21163	-2.31862			
455	-0.29539	-13.9421			
456	-1.04464	-4.54301			
457	-0.99813	10.76472			
458	-0.31221	-8.55918			
459	-0.24674	-4.585			
460	0.08234	-7.53592			
461	-1.06453	-5.59987			
462	-0.88576	3.889287			
463	-0.38029	4.286178			
464	0.194675	1.829354			
465	0.722271	-8.99744			
466	0.014846	-6.29933			
467	-0.47005	-11.7089			
468	-1.40609	-8.14543			
469	-1.39369	10.18273			
470	-0.43807	-0.32857			
471	-0.01297	-3.9748			
472	0.467131	2.419655			
473	0.16111	-6.7201			
474	-0.32701	-3.82125			
475	-0.19343	-2.86819			
476	-0.59923	-2.05522			
477	-0.36881	0.9604			
478	-0.06872	-0.13344			
479	0.061555	0.285334			
480	0.262987	6.848291			
481	0.681848	-0.51793			
482	0.588486	8.417009			
483	1.256093	4.044373			
484	1.004177	7.468911			
485	1.588039	8.039269			
486	1.583899	-6.93229			
487	0.859784	1.055795			
488	0.684655	-0.00264			
489	0.014067	-11.3438			
490	-0.37456	5.188714			
491	0.023876	-3.73196			

492	-0.50868	-9.32378			
493	-0.30646	1.431723			
494	-0.42072	5.959551			
495	0.011877	0.36666			
496	0.575533	-5.19019			
497	0.277303	-10.0827			
498	-0.62696	6.602113			
499	-0.15928	-6.30812			
500	-0.53734	-1.23021			
501	0.160556	1.625291			
502	-0.16173	2.252641			
503	0.324769	0.41181			
504	0.474081	2.910185			
505	0.600989	-4.89527			
506	0.141702	1.458892			
507	0.322891	-4.14045			
508	-0.22909	-1.09773			
509	0.04251	-0.82682			
510	-0.14209	1.473754			
511	0.178816	-2.12786			
512	0.100492	0.634855			
513	0.250579	-3.65439			
514	-0.09652	0.403418			
515	0.114941	-1.05455			
516	-0.04744	1.490541			
517	0.281197	3.633543			
518	0.479455	1.358243			
519	0.612531	-0.74953			
520	0.538438	1.992566			
521	0.487163	2.268942			
522	0.506594	-1.62797			
523	0.431501	0.441138			
524	0.38893	-1.18454			
525	0.132586	-0.39876			
526	0.211927	4.964128			
527	0.488493	1.057795			
528	0.546998	2.683568			
529	0.823733	2.656454			
530	0.69338	4.799121			
531	0.942738	0.093744			
532	0.764186	-2.88924			
533	0.468891	-3.98621			
534	-0.05446	3.947717			
535	0.164303	0.739485			
536	0.238956	-3.78988			
537	0.268851	-2.54089			

538	-0.05017	-0.06332			
539	-0.12709	-2.70657			
540	-0.12048	1.832921			
541	0.181031	-2.95523			
542	-0.06377	0.33928			
543	0.204619	-2.84261			
544	-0.12045	1.252136			
545	0.176931	1.510398			
546	0.212168	2.138745			
547	0.519068	-0.84546			
548	0.410947	-3.45852			
549	0.145559	0.232346			
550	0.070098	-3.44173			
551	-0.18064	0.045844			
552	0.065173	-1.89269			
553	-0.12478	-3.33308			
554	-0.10977	-1.22423			
555	-0.15587	1.736588			
556	0.034762	3.048586			
557	0.406977	4.937203			
558	0.810296	-1.17183			
559	0.640717	-0.41965			
560	0.545507	-1.90399			
561	0.112068	0.221665			
562	0.183075	-0.28143			
563	0.13728	0.126213			
564	0.246351	-0.45521			
565	0.205796	-0.29269			
566	0.213703	2.59166			
567	0.379005	-4.27491			

Sours: Calculated using Excel 2007

Appendix 7-3: The calculation of $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ and ε_t (abnormal returns (Residuals)) and the Weekly positive and negative abnormal returns for the period 2000-2004.

	Coefficients	*Standard Error*	*t Stat*	*P-value*
α_0	0.513207	0.185151	2.771823	0.005994
α_1	-0.01191	0.063026	-0.18903	0.850224
α_2	0.076512	0.062846	1.217449	0.224581
α_3	0.014321	0.063108	0.226925	0.820667

RESIDUAL OUTPUT					
Observation	*Predicted Y*	*Residuals*		*Positive*	*Negative*
1	0.579475	2.63895		3	2
2	0.821768	2.766758		1	1
3	0.77813	3.862544		2	5
4	0.778576	-5.19222		2	1
5	0.972247	-1.30331		2	1
6	0.245912	0.446035		4	2
7	0.416426	-2.64076		1	2
8	0.587908	0.167067		2	1
9	0.343933	1.29145		1	3
10	0.519634	-2.25675		3	3
11	0.669841	-0.58488		1	1
12	0.402704	-1.01752		6	4
13	0.502155	-0.00199		1	1
14	0.461424	-0.28848		2	3
15	0.54061	0.395197		1	1
16	0.522453	2.250523		1	1
17	0.554248	-0.95629		1	1
18	0.743564	0.055337		2	2
19	0.512639	0.43628		3	2
20	0.55727	-0.53666		1	4
21	0.597006	1.867106		1	4
22	0.499017	1.082229		2	5
23	0.683198	0.428631		1	3
24	0.656233	5.276788		1	3
25	0.550236	-2.85365		1	5
26	1.010519	-0.49568		2	1
27	0.4158	6.133188		1	3
28	0.44159	-3.49445		1	2
29	1.058027	-0.70164		2	1
30	0.369167	3.028427		3	1
31	0.456278	1.127146		1	1

32	0.759403	-2.68593		1	1
33	0.705966	0.836216		1	2
34	0.370107	-0.30932		1	4
35	0.602889	-2.26339		1	3
36	0.559726	-1.79074		2	1
37	0.401695	0.203988		2	3
38	0.388024	0.0055		4	2
39	0.537231	0.837508		2	5
40	0.535612	-1.57447		1	4
41	0.636403	-2.05753		2	1
42	0.47034	-1.50154		2	1
43	0.401882	0.427823		2	6
44	0.404071	-1.28849		4	3
45	0.572458	0.952567		5	1
46	0.439252	1.837302		3	2
47	0.590102	4.138448		1	1
48	0.652896	3.769697		6	1
49	0.854911	1.27247		1	1
50	0.893961	7.508917		1	1
51	0.639204	-0.13558		1	2
52	1.180594	-4.01258		3	3
53	0.705816	-1.07222		2	1
54	0.308104	-0.82356		3	5
55	0.450757	2.906926		2	2
56	0.428519	-0.25471		1	4
57	0.760658	3.080252		2	1
58	0.528831	0.44462		4	4
59	0.797975	-2.43249		1	1
60	0.662166	-2.6851			
61	0.426187	-0.27433			
62	0.333211	1.668501			
63	0.472008	-0.73023			
64	0.671613	1.39046			
65	0.497549	-0.88716			
66	0.671924	1.935665			
67	0.481862	-4.76148			
68	0.758125	5.879554			
69	0.144029	1.149395			
70	0.944372	-0.60107			
71	0.703136	-0.56989			
72	0.556409	0.100302			
73	0.520494	3.261925			
74	0.520299	2.624458			
75	0.774547	-2.71792			
76	0.831139	-3.47226			
77	0.441016	2.261623			

78	0.2511	-2.38392			
79	0.707578	-1.02025			
80	0.392449	-2.67628			
81	0.485949	-0.09696			
82	0.329354	1.339924			
83	0.490376	-1.05077			
84	0.653174	-1.55502			
85	0.504979	-1.0385			
86	0.442535	-0.14816			
87	0.455964	1.208097			
88	0.508265	6.240053			
89	0.564347	-0.62522			
90	1.054091	-0.92971			
91	0.603709	-1.41627			
92	0.531532	-1.34166			
93	0.462469	-0.06428			
94	0.434842	0.373864			
95	0.522437	-0.22656			
96	0.57726	-3.16286			
97	0.57823	-1.33167			
98	0.328591	0.543302			
99	0.408144	-0.35861			
100	0.568537	-0.23523			
101	0.525512	-0.75798			
102	0.542188	0.428911			
103	0.488624	-2.82694			
104	0.612036	-1.74047			
105	0.361648	-2.00498			
106	0.412959	-3.05271			
107	0.402761	-0.04159			
108	0.283397	5.054492			
109	0.439444	5.240578			
110	0.859123	-2.98882			
111	1.049612	1.366703			
112	0.402815	-2.57271			
113	0.693436	-1.41655			
114	0.390402	-0.83599			
115	0.432114	4.508709			
116	0.409895	-1.58895			
117	0.898905	-1.68047			
118	0.503063	0.892654			
119	0.419895	0.244558			
120	0.600887	-2.84338			
121	0.610749	0.159186			
122	0.341972	1.828151			
123	0.514148	5.53253			

124	0.618236	-3.71864			
125	1.043865	1.817276			
126	0.328496	-0.31804			
127	0.687594	1.51983			
128	0.528682	-3.15089			
129	0.713491	1.677314			
130	0.315705	2.134679			
131	0.629387	-2.81456			
132	0.760962	-2.04711			
133	0.396429	1.062475			
134	0.366127	-3.70059			
135	0.646137	-1.70872			
136	0.291632	-2.00992			
137	0.404625	-0.90044			
138	0.372427	0.21176			
139	0.443704	-0.83529			
140	0.555469	-1.01581			
141	0.497096	-4.82872			
142	0.523982	0.229697			
143	0.166214	0.458113			
144	0.501402	-1.32627			
145	0.581596	0.102941			
146	0.45088	0.297009			
147	0.544859	-0.68434			
148	0.581894	-0.25846			
149	0.509392	-1.19102			
150	0.544076	1.837204			
151	0.437316	2.640542			
152	0.648974	3.111139			
153	0.738006	4.308371			
154	0.784858	-2.28043			
155	0.970981	-0.23022			
156	0.46222	2.987188			
157	0.507372	3.475708			
158	0.740284	-1.65614			
159	0.87827	-4.19246			
160	0.539657	-0.04122			
161	0.240577	-0.7712			
162	0.510203	-1.50235			
163	0.491566	0.067126			
164	0.423041	-0.99208			
165	0.548525	-0.01109			
166	0.471266	-1.08635			
167	0.553506	-2.23953			
168	0.493929	0.889077			
169	0.35892	0.761901			

170	0.581525	-0.69238			
171	0.62009	1.4813			
172	0.495741	0.816235			
173	0.656771	-0.18437			
174	0.638055	0.795839			
175	0.551057	0.237757			
176	0.620285	-0.22235			
177	0.589354	-0.48135			
178	0.553664	-0.34007			
179	0.524625	-1.61524			
180	0.544089	-2.58951			
181	0.457188	-1.62142			
182	0.354959	1.88029			
183	0.368207	2.411889			
184	0.634437	4.390411			
185	0.698064	0.993878			
186	0.917325	-0.67748			
187	0.711763	-0.26353			
188	0.550447	-0.51377			
189	0.5505	1.344273			
190	0.499859	2.593867			
191	0.621848	5.294757			
192	0.706561	4.50608			
193	0.948102	0.566736			
194	0.97872	-1.13841			
195	0.705662	4.865886			
196	0.456305	1.109769			
197	0.918553	2.80568			
198	0.668451	-6.15732			
199	0.885975	-8.11212			
200	0.232665	7.896151			
201	-0.21513	-4.16135			
202	1.083815	0.930194			
203	0.270771	2.467986			
204	0.572	2.959724			
205	0.709522	2.714694			
206	0.781853	2.962914			
207	0.781164	0.448612			
208	0.834113	-0.08252			
209	0.651974	8.280255			
210	0.481909	-2.98808			
211	1.237251	2.001055			
212	0.410792	-8.32087			
213	0.819323	0.838756			
214	-0.06539	-2.97698			
215	0.563037	-0.42927			

216	0.30258	1.055824			
217	0.463689	6.082315			
218	0.54107	4.358061			
219	0.975142	-0.90927			
220	0.981009	-2.24159			
221	0.603424	-0.65384			
222	0.418301	5.457982			
223	0.421289	0.181488			
224	0.95491	-1.76896			
225	0.653178	1.362825			
226	0.435537	2.95067			
227	0.615456	5.795088			
228	0.724791	-7.8683			
229	1.137289	-3.03554			
230	0.081061	-1.3992			
231	0.281371	-1.75615			
232	0.402739	-2.13379			
233	0.402115	0.539485			
234	0.348423	0.169625			
235	0.554289	-2.81957			
236	0.593316	-13.6458			
237	0.502807	5.549918			
238	-0.59002	-4.88829			
239	0.854657	-2.34541			
240	0.19849	-1.99835			
241	0.342135	-0.905			
242	0.360853	0.315534			
243	0.436307	0.030594			
244	0.551335	-0.49751			
245	0.557975	0.96029			
246	0.505924	0.124199			
247	0.622636	1.45163			
248	0.55845	1.564441			
249	0.655646	-3.11504			
250	0.734639	-0.97225			
251	0.358266	-2.91257			
252	0.490237	-2.20499			
253	0.334798	1.146884			
254	0.327775	-0.59922			

Sours: Calculated using Excel 2007

Appendix 7-4: The calculation of $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ and ε_t (abnormal returns (Residuals)) and the Monthly positive and negative abnormal returns for the period 2005-2010.

	Coefficients	*Standard Error*	*t Stat*	*P-value*
α_0	0.007092	0.202386	0.035042	0.972069
α_1	0.100177	0.057084	1.754898	0.080278
α_2	0.018412	0.057437	0.320561	0.748762
α_3	0.084558	0.057045	1.482288	0.139293

RESIDUAL OUTPUT					
Observation	*Predicted Y*	*Residuals*		*Positive*	*Negative*
1	0.227348	0.165871		1	2
2	0.026916	-2.86105		1	3
3	-0.34234	-2.44284		1	3
4	-0.29085	2.920224		3	5
5	-0.02044	-1.12271		3	3
6	-0.29452	-2.8068		1	1
7	-0.1023	-4.10086		2	1
8	-0.56773	1.839446		3	1
9	-0.20514	-1.75613		3	1
10	-0.52138	-0.80317		2	1
11	-0.05417	-0.07273		1	1
12	-0.19585	1.523966		1	2
13	0.025801	1.045743		1	1
14	0.128159	5.183194		4	1
15	0.671197	-1.4205		1	1
16	0.12043	-1.02662		2	4
17	0.351633	-1.21291		1	1
18	-0.15923	-0.74144		1	1
19	-0.17562	-0.87758		6	1
20	-0.18782	0.473024		1	1
21	-0.05989	0.838987		5	1
22	0.001335	1.294473		3	1
23	0.175362	-0.50645		3	2
24	0.063662	-1.00711		2	2
25	0.016055	-0.79219		1	3
26	-0.11603	0.796397		4	1
27	-0.01882	-0.37073		7	2
28	-0.08503	1.877743		7	1
29	0.237038	0.558024		1	1
30	0.086807	-1.68515		5	1
31	0.013202	1.122686		3	1

32	0.158681	0.956349		2	3
33	0.004554	7.911893		2	3
34	0.916713	-2.99664		3	2
35	0.038775	1.755647		3	1
36	0.817952	1.233111		1	1
37	0.069726	0.52222		3	3
38	0.255888	-0.38343		6	4
39	0.178648	0.968602		1	3
40	0.169725	5.049586		1	4
41	0.540284	-2.04031		1	1
42	0.049932	1.125032		2	3
43	0.53851	-2.26159		1	3
44	-0.27073	0.14219		2	9
45	0.061842	-1.80869		1	4
46	-0.31597	-4.25568		3	4
47	-0.49391	1.740758		1	2
48	-0.09989	-2.62464		1	4
49	-0.62945	0.656837		4	1
50	0.065102	1.383115		4	1
51	-0.07771	0.160708		1	2
52	0.044387	0.102772		1	2
53	0.14582	-1.50835		3	2
54	-0.11967	0.188935		1	2
55	0.001387	-0.75069		4	1
56	-0.18191	1.443931		1	3
57	0.125577	0.456771		1	1
58	0.025307	-0.60766		1	1
59	0.06619	-0.5336		1	1
60	-0.00121	-1.27271		3	1
61	-0.17837	-0.39377		2	1
62	-0.1132	0.113202		1	2
63	-0.11116	-0.18493		6	2
64	-0.07095	0.082088		2	2
65	0.002756	-0.50833		1	1
66	-0.06839	0.304956		1	1
67	0.022424	0.083632		1	1
68	-0.02068	2.803344		3	2
69	0.307806	1.02764		1	1
70	0.201075	0.452851		1	3
71	0.332484	0.412687		3	3
72	0.206703	-0.24936		1	1
73	0.071834	1.116008		1	2
74	0.188311	-0.81137		1	1
75	-0.03706	3.674467			
76	0.460444	1.44006			
77	0.211766	1.834344			

78	0.554628	1.070916			
79	0.368309	0.864685			
80	0.333553	-1.06815			
81	0.093657	5.757402			
82	0.683965	8.564772			
83	0.979213	9.054396			
84	1.677266	-14.2513			
85	-0.28574	4.750429			
86	1.071253	1.324582			
87	-0.73393	1.375255			
88	0.492974	-0.85963			
89	0.184756	-2.18521			
90	-0.14583	0.478256			
91	-0.02744	2.57411			
92	0.099175	-2.05396			
93	-0.11373	-0.51152			
94	0.123805	2.5192			
95	0.095054	-0.521			
96	-0.03978	-2.46834			
97	-0.02852	-3.72854			
98	-0.45147	1.327188			
99	-0.18644	2.245547			
100	-0.0882	1.586339			
101	0.269132	1.378397			
102	0.373833	-0.77436			
103	0.123982	1.110333			
104	0.262678	2.005354			
105	0.223154	3.232636			
106	0.499411	0.38312			
107	0.350909	6.553522			
108	1.007217	0.813229			
109	0.391208	4.79578			
110	1.144048	-2.51348			
111	0.119343	-1.01019			
112	0.331236	1.56381			
113	0.064733	0.386996			
114	0.011909	1.674458			
115	0.344585	3.082388			
116	0.419641	2.275876			
117	0.482813	2.31506			
118	0.626781	1.917778			
119	0.541439	-0.47606			
120	0.297074	0.334147			
121	0.286692	-1.05488			
122	-0.05271	0.519742			
123	0.093108	2.100102			

124	0.170443	4.765873			
125	0.581468	0.53237			
126	0.395014	0.304098			
127	0.515039	-2.97807			
128	-0.13259	1.873133			
129	0.195219	0.076378			
130	-0.14192	0.227372			
131	0.167829	-1.00469			
132	-0.0522	1.623819			
133	0.156348	3.362541			
134	0.317776	-0.19489			
135	0.217085	-2.91105			
136	0.037032	-4.1144			
137	-0.44057	0.432621			
138	-0.29657	4.504557			
139	0.083714	-0.44354			
140	0.047851	-2.60122			
141	0.100497	-1.51885			
142	-0.21243	1.569326			
143	-0.099	0.693709			
144	-0.02828	0.219434			
145	0.151927	-1.29273			
146	-0.05338	-0.44436			
147	-0.04761	2.229729			
148	0.120061	3.112416			
149	0.329	3.217313			
150	0.606381	-2.4813			
151	0.157895	0.579371			
152	0.346296	-0.59316			
153	-0.1626	0.570354			
154	0.105736	3.811844			
155	0.386175	3.048843			
156	0.45781	-1.68862			
157	0.278301	-0.13906			
158	0.288837	-0.91991			
159	-0.15764	2.346473			
160	0.226517	5.349496			
161	0.552617	1.142254			
162	0.464628	0.387285			
163	0.595135	1.753079			
164	0.401328	0.311257			
165	0.193748	-1.89656			
166	0.04819	-1.62817			
167	-0.12228	-1.1984			
168	-0.29829	-1.17273			
169	-0.29818	2.697778			

170	0.108717	-3.81191			
171	-0.44408	-1.22943			
172	-0.02583	-2.10737			
173	-0.55055	6.130952			
174	0.385332	-0.55022			
175	-0.08706	-2.9132			
176	0.175367	-2.9225			
177	-0.33729	-4.34389			
178	-0.76613	7.567587			
179	0.369957	-10.5199			
180	-1.28029	2.237773			
181	0.491243	0.507665			
182	-0.73347	-0.70955			
183	-0.03811	-4.40437			
184	-0.38004	-3.25019			
185	-0.56039	4.86671			
186	-0.004	-5.73893			
187	-0.79589	-3.7012			
188	-0.18502	-6.69857			
189	-1.25089	8.703805			
190	0.246693	3.503874			
191	-0.06203	-1.7224			
192	0.527592	-3.48484			
193	-0.00487	-2.35117			
194	-0.43426	-0.66161			
195	-0.39613	-2.55968			
196	-0.50841	-2.75185			
197	-0.4666	-2.06366			
198	-0.55635	-13.6812			
199	-1.74144	-3.84621			
200	-1.02876	10.79535			
201	-0.3213	-8.55009			
202	-1.17427	-3.65747			
203	0.185565	-7.63914			
204	-1.57869	-5.08571			
205	-1.20632	4.209853			
206	-0.44499	4.350879			
207	-0.10985	2.133883			
208	0.53574	-8.81091			
209	-0.45435	-5.83014			
210	-0.60368	-11.5753			
211	-2.02839	-7.52312			
212	-1.70539	10.49443			
213	-0.31814	-0.44851			
214	-0.71554	-3.27223			
215	0.336676	2.55011			

216	0.158031	-6.71703			
217	-0.93401	-3.21425			
218	-0.28513	-2.77649			
219	-0.9306	-1.72384			
220	-0.66596	1.257553			
221	-0.2414	0.039241			
222	-0.22672	0.573611			
223	0.088144	7.023135			
224	0.708768	-0.54485			
225	0.183779	8.821717			
226	1.513563	3.786903			
227	0.717746	7.755342			
228	1.714974	7.912333			
229	1.575726	-6.92412			
230	0.365033	1.550546			
231	0.914576	-0.23256			
232	-0.34156	-10.9881			
233	-0.95334	5.767494			
234	0.338423	-4.04651			
235	-1.23374	-8.59871			
236	-0.63909	1.764349			
237	-0.37477	5.913596			
238	-0.24874	0.627276			
239	0.242144	-4.8568			
240	0.020133	-9.82548			
241	-1.02813	7.003287			
242	0.034921	-6.50232			
243	-1.35989	-0.40766			
244	0.216191	1.569655			
245	-0.39342	2.484337			
246	0.099974	0.636605			
247	0.270385	3.11388			
248	0.536481	-4.83077			
249	-0.2985	1.899093			
250	0.374533	-4.19209			
251	-0.70898	-0.61784			
252	-0.06077	-0.72354			
253	-0.41871	1.750376			
254	0.01386	-1.9629			
255	-0.22996	0.965304			
256	0.157473	-3.56128			
257	-0.48516	0.792056			
258	0.037344	-0.97695			
259	-0.3692	1.812299			
260	0.160307	3.754433			
261	0.346377	1.491321			

262	0.38529	-0.52229			
263	0.358226	2.172777			
264	0.413508	2.342597			
265	0.318206	-1.43959			
266	0.159518	0.713122			
267	0.306913	-1.10252			
268	-0.15136	-0.11481			
269	0.039567	5.136488			
270	0.453436	1.092852			
271	0.234789	2.995777			
272	0.796865	2.683321			
273	0.545957	4.946543			
274	0.894559	0.141923			
275	0.506329	-2.63138			
276	0.277729	-3.79505			
277	-0.29675	4.189999			
278	0.152654	0.751135			
279	-0.1281	-3.42282			
280	-0.00278	-2.26925			
281	-0.20947	0.095978			
282	-0.34637	-2.48729			
283	-0.47098	2.183424			
284	0.116868	-2.89107			
285	-0.4789	0.754407			
286	0.128413	-2.7664			
287	-0.48668	1.618363			
288	0.095186	1.592143			
289	-0.0261	2.377016			
290	0.369358	-0.69575			
291	0.160358	-3.20793			
292	-0.10543	0.48333			
293	-0.03876	-3.33287			
294	-0.5814	0.446608			
295	-0.03654	-1.79098			
296	-0.46356	-2.9943			
297	-0.38435	-0.94965			
298	-0.34474	1.925458			
299	-0.15151	3.234856			
300	0.232275	5.111904			
301	0.732886	-1.09442			
302	0.329993	-0.10893			
303	0.474473	-1.83295			
304	-0.1555	0.489229			
305	0.034205	-0.13256			
306	-0.11149	0.374979			
307	0.059897	-0.26876			

308	-0.0173	-0.0696			
309	0.016822	2.788541			
310	0.268863	-4.16476			

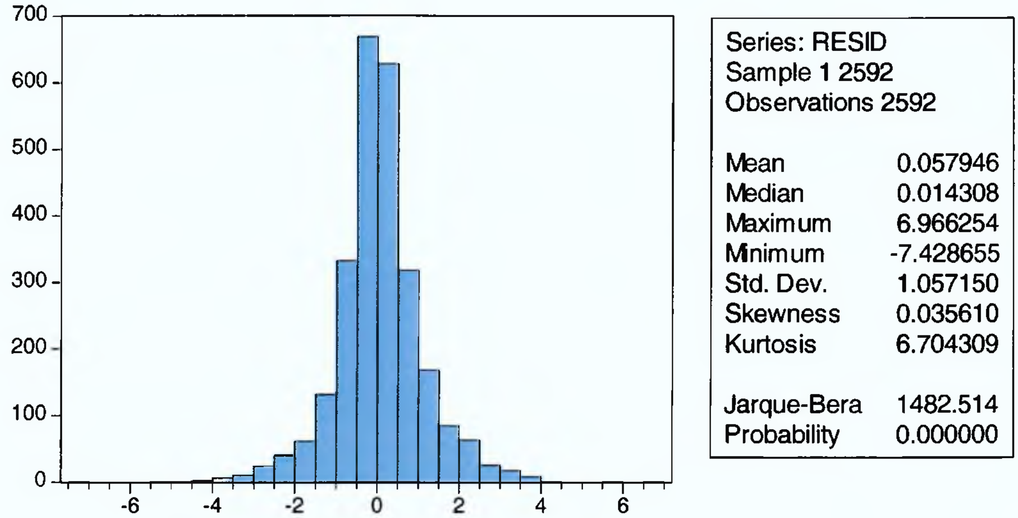
Sours: Calculated using Excel 2007

Appendix 7-5: Eviews command

Log-Logistic command which has been adopted from http://forums.eviews.com/viewforum.php?f=5 and tested on date collected from several previous studies such as McQueen and Thorley (1994) and Zhao (2007)

```
@logl log1
log1=ni*log(1-@LOGIT(-(C(1) + C(2)*log(RUN))))+mi*log(1-(1-@LOGIT(-
(C(1)+C(2)*log(RUN)))))
```

Appendix 9-1a: Histogram and statistical analysis of the model residuals (2000-2010)



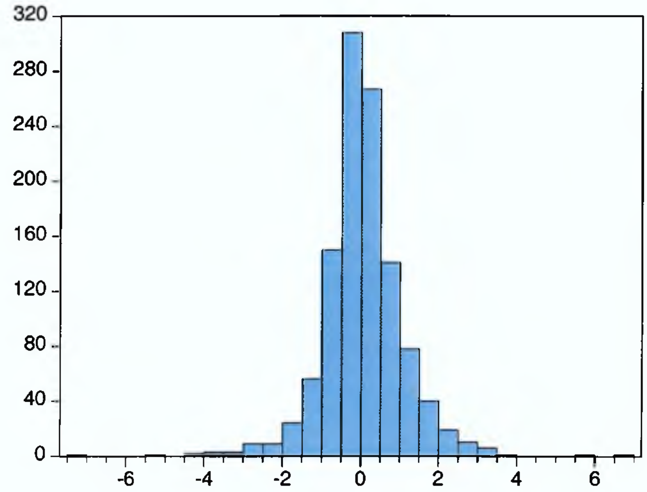
Descriptive statistics of the residuals of returns for the NSM all Share Index
Result of the Ljung-Box Q statistics (2000- 2010)

Date: 03/05/12 Time: 18:36
Sample: 1 2592
Included observations: 2592

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|*** |	|*** |	1	0.478	0.478	592.64	0.000
|** |	| |	2	0.224	-0.006	722.94	0.000
| |	*| |	3	0.038	-0.087	726.69	0.000
| |	| |	4	-0.056	-0.053	734.87	0.000
*| |	| |	5	-0.068	-0.005	746.95	0.000
| |	| |	6	-0.046	0.006	752.53	0.000
| |	| |	7	-0.039	-0.022	756.42	0.000
| |	| |	8	0.003	0.030	756.44	0.000
| |	| |	9	0.023	0.012	757.76	0.000
| |	| |	10	0.023	-0.002	759.18	0.000

Ljung-Box-Pierce portmanteau tests for up to 10 order serial correlation in the squared residuals of the NSM for overall period.

Appendix 9-1b: Histogram and statistical analysis of the model residuals (2000-2004)



Series: RESID	
Sample 1/03/2000 12/31/2004	
Observations 1130	
Mean	0.059248
Median	-0.000690
Maximum	6.999338
Minimum	-7.326352
Std. Dev.	1.038021
Skewness	-0.062005
Kurtosis	9.358153
Jarque-Bera	1904.120
Probability	0.000000

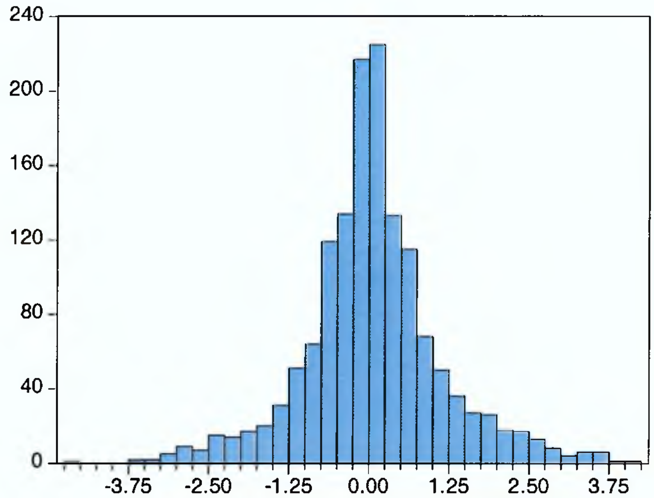
Descriptive statistics of the residuals of returns for the NSM all Share Index
Result of the Ljung-Box Q statistics (pre-reforms periods)

Date: 03/11/12 Time: 13:26
Sample: 1/03/2000 12/31/2004
Included observations: 1130

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|** |	|** |	1	0.350	0.350	139.07	0.000
|* |	| |	2	0.160	0.042	167.98	0.000
| |	| |	3	0.028	-0.046	168.85	0.000
*| |	*| |	4	-0.092	-0.108	178.39	0.000
*| |	| |	5	-0.100	-0.037	189.71	0.000
| |	| |	6	-0.061	0.007	193.98	0.000
| |	| |	7	-0.013	0.023	194.17	0.000
| |	| |	8	0.065	0.066	198.99	0.000
|* |	| |	9	0.075	0.021	205.33	0.000
| |	| |	10	0.052	-0.003	208.44	0.000

Ljung-Box-Pierce portmanteau tests for up to 10 order serial correlation in the squared residuals of the NSM for pre-reforms period

Appendix 9-1c: Histogram and statistical analysis of the model residuals (2005-2010)



Series: RESID	
Sample 1 1462	
Observations 1462	
Mean	0.061467
Median	0.026419
Maximum	4.234762
Minimum	-4.731698
Std. Dev.	1.075016
Skewness	0.156715
Kurtosis	4.757215
Jarque-Bera	194.0832
Probability	0.000000

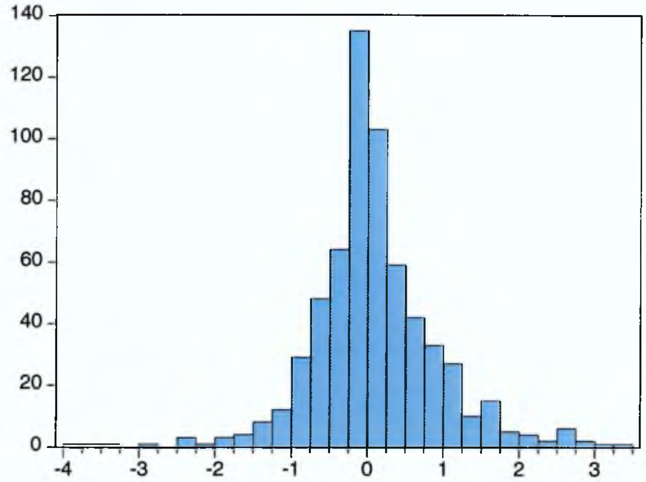
Descriptive statistics of the residuals of returns for the NSM all Share Index
Result of the Ljung-Box Q statistics (post-reforms)

Date: 03/11/12 Time: 13:48
Sample: 1 1462
Included observations: 1462

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|**** |	|**** |	1	0.585	0.585	501.80	0.000
|** |	*| |	2	0.291	-0.078	626.15	0.000
|* |	*| |	3	0.074	-0.098	634.20	0.000
| |	| |	4	0.002	0.028	634.21	0.000
| |	| |	5	-0.010	0.010	634.36	0.000
| |	| |	6	-0.005	-0.004	634.40	0.000
| |	| |	7	-0.030	-0.046	635.73	0.000
| |	| |	8	-0.012	0.038	635.94	0.000
| |	| |	9	0.017	0.032	636.39	0.000
| |	| |	10	0.036	0.005	638.35	0.000

Ljung-Box-Pierce portmanteau tests for up to 10 order serial correlation in the squared residuals of the NSM for post-reforms period.

Appendix 9-1d: Histogram and statistical analysis of the model residuals (2005-July 2007)



Series: RESID	
Sample 1/04/2005 7/31/2007	
Observations 621	
Mean	0.090399
Median	-0.000359
Maximum	3.469182
Minimum	-3.806650
Std. Dev.	0.837738
Skewness	0.131117
Kurtosis	6.163645
Jarque-Bera	260.7531
Probability	0.000000

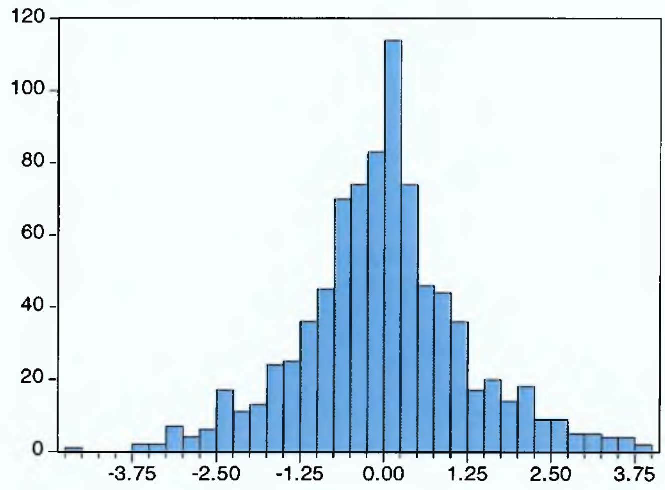
Descriptive statistics of the residuals of returns for the NSM all Share Index
Result of the Ljung-Box Q statistics

Date: 03/05/12 Time: 18:28
Sample: 1/04/2005 7/31/2007
Included observations: 621

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|**** |</td><td>.|**** |</td><td>1</td><td>0.523</td><td>0.523</td><td>170.36</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>*|. |</td><td>2</td><td>0.176</td><td>-0.133</td><td>189.75</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>3</td><td>-0.046</td><td>-0.114</td><td>191.10</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>4</td><td>-0.112</td><td>-0.020</td><td>198.91</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>-0.058</td><td>0.044</td><td>201.05</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.001</td><td>0.011</td><td>201.05</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>0.025</td><td>-0.006</td><td>201.44</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>8</td><td>0.077</td><td>0.078</td><td>205.21</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>9</td><td>0.094</td><td>0.032</td><td>210.77</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>0.049</td><td>-0.031</td><td>212.29</td><td>0.000</td></tr>
</table>

Ljung-Box-Pierce portmanteau tests for up to 10 order serial correlation in the squared residuals of the NSM for pre-crisis period.

Appendix 9-1e: Histogram and statistical analysis of the model residuals (August 2007-2010)



Series: RESID	
Sample 1 841	
Observations 841	
Mean	-0.014427
Median	0.004805
Maximum	3.897591
Minimum	-4.648932
Std. Dev.	1.238527
Skewness	0.117280
Kurtosis	3.856945
Jarque-Bera	27.66095
Probability	0.000001

Descriptive statistics of the residuals of returns for the NSM all Share Index

Result of the Ljung-Box Q statistics

Date: 03/05/12 Time: 18:34
Sample: 1 841
Included observations: 841

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|**** |	.|**** |	1	0.600	0.600	303.87	0.000
.|** |	.| |	2	0.324	-0.057	392.40	0.000
.|* |	*| |	3	0.104	-0.105	401.61	0.000
.| |	.| |	4	0.026	0.032	402.19	0.000
.| |	.| |	5	-0.006	-0.005	402.23	0.000
.| |	.| |	6	-0.021	-0.020	402.59	0.000
.| |	.| |	7	-0.058	-0.057	405.44	0.000
.| |	.| |	8	-0.056	0.011	408.15	0.000
.| |	.| |	9	-0.025	0.033	408.69	0.000
.| |	.| |	10	0.017	0.026	408.93	0.000

Ljung-Box-Pierce portmanteau tests for up to 10 order serial correlation in the squared residuals of the NSM for post-crisis period.

Appendix 9-2a: Estimation results of the GARCH (1,1) For 2000-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/20/12 Time: 22:17
Sample: 1 2592
Included observations: 2592
Convergence achieved after 21 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.046870	0.017244	2.718017	0.0066
M9	-0.159737	0.052871	-3.021258	0.0025
Y00	0.134817	0.049754	2.709654	0.0067
Y08	-0.340547	0.052478	-6.489350	0.0000
Y09	-0.204604	0.058367	-3.505491	0.0005
Variance Equation				
C	0.148469	0.018004	8.246415	0.0000
RESID(-1)^2	0.532234	0.059009	9.019600	0.0000
GARCH(-1)	0.426540	0.035879	11.88835	0.0000
T-DIST. DOF	5.563568	0.570934	9.744672	0.0000

R-squared	0.012361	Mean dependent var	0.059927
Adjusted R-squared	0.009302	S.D. dependent var	1.071256
S.E. of regression	1.066261	Akaike info criterion	2.565079
Sum squared resid	2936.648	Schwarz criterion	2.585427
Log likelihood	-3315.342	Hannan-Quinn criter.	2.572453
F-statistic	4.041098	Durbin-Watson stat	1.029714
Prob(F-statistic)	0.000087		

Appendix 9-2b: Estimation results of the EGARCH (1,1) For 2000-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:18
Sample: 1 2592
Included observations: 2592
Convergence achieved after 13 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.063608	0.014853	4.282435	0.0000
Y08	-0.408662	0.049243	-8.298845	0.0000
Y09	-0.241149	0.060648	-3.976191	0.0001
		Variance Equation		
C(4)	-0.528541	0.033819	-15.62836	0.0000
C(5)	0.660400	0.048964	13.48759	0.0000
C(6)	0.071339	0.025335	2.815819	0.0049
C(7)	0.824934	0.020872	39.52386	0.0000
T-DIST. DOF	5.983780	0.648661	9.224815	0.0000

R-squared	0.011733	Mean dependent var	0.059927
Adjusted R-squared	0.009056	S.D. dependent var	1.071256
S.E. of regression	1.066394	Akaike info criterion	2.570415
Sum squared resid	2938.517	Schwarz criterion	2.588502
Log likelihood	-3323.258	Hannan-Quinn criter.	2.576970
F-statistic	4.382480	Durbin-Watson stat	1.029062
Prob(F-statistic)	0.000076		

Appendix 9-2c: Estimation results of the GARCH-M (1,1) For 2000-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:20
Sample: 1 2592
Included observations: 2592
Convergence achieved after 18 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(7) + C(8)*RESID(-1)^2 + C(9)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.156987	0.051034	3.076112	0.0021
C	-0.077208	0.041209	-1.873562	0.0610
M9	-0.157443	0.052265	-3.012363	0.0026
Y00	0.137692	0.049427	2.785750	0.0053
Y08	-0.360228	0.052204	-6.900401	0.0000
Y09	-0.277765	0.058922	-4.714080	0.0000
		Variance Equation		
C	0.148370	0.018062	8.214515	0.0000
RESID(-1)^2	0.524812	0.058573	8.959985	0.0000
GARCH(-1)	0.431265	0.035910	12.00967	0.0000
T-DIST. DOF	5.507262	0.558432	9.862003	0.0000

R-squared	0.019935	Mean dependent var	0.059927
Adjusted R-squared	0.016519	S.D. dependent var	1.071256
S.E. of regression	1.062371	Akaike info criterion	2.562047
Sum squared resid	2914.128	Schwarz criterion	2.584656
Log likelihood	-3310.413	Hannan-Quinn criter.	2.570240
F-statistic	5.835437	Durbin-Watson stat	1.031979
Prob(F-statistic)	0.000000		

Appendix 9-2d: Estimation results of the GJR-GARCH (1,1) For 2000-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:22
Sample: 1 2592
Included observations: 2592
Convergence achieved after 17 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0) + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.065314	0.016525	3.952525	0.0001
M9	-0.145630	0.052329	-2.782944	0.0054
Y08	-0.372469	0.052447	-7.101770	0.0000
Y09	-0.232138	0.057710	-4.022471	0.0001
Variance Equation				
C	0.147499	0.017601	8.380343	0.0000
RESID(-1)^2	0.593659	0.072831	8.151137	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.154542	0.073512	-2.102258	0.0355
GARCH(-1)	0.431881	0.035421	12.19275	0.0000
T-DIST. DOF	5.735439	0.600999	9.543175	0.0000

R-squared	0.012441	Mean dependent var	0.059927
Adjusted R-squared	0.009383	S.D. dependent var	1.071256
S.E. of regression	1.066218	Akaike info criterion	2.565774
Sum squared resid	2936.409	Schwarz criterion	2.586122
Log likelihood	-3316.243	Hannan-Quinn criter.	2.573148
F-statistic	4.067619	Durbin-Watson stat	1.029759
Prob(F-statistic)	0.000080		

Appendix 9-2e: Estimation results of the PGARCH (1,1) For 2000-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:24
Sample: 1 2592
Included observations: 2592
Convergence achieved after 24 iterations
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(11) = C(7) + C(8)*(ABS(RESID(-1)) - C(9)*RESID(
-1))^C(11) + C(10)*@SQRT(GARCH(-1))^C(11)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.038016	0.018088	2.101737	0.0356
M9	-0.150472	0.051253	-2.935860	0.0033
Y00	0.144942	0.049839	2.908223	0.0036
Y03	0.137284	0.052555	2.612218	0.0090
Y08	-0.334393	0.052461	-6.374176	0.0000
Y09	-0.194275	0.058924	-3.297051	0.0010
		Variance Equation		
C(7)	0.152914	0.021230	7.202646	0.0000
C(8)	0.479665	0.055727	8.607462	0.0000
C(9)	-0.077271	0.038312	-2.016918	0.0437
C(10)	0.472327	0.040100	11.77874	0.0000
C(11)	1.641520	0.264133	6.214738	0.0000
T-DIST. DOF	5.717142	0.595824	9.595359	0.0000

R-squared	0.014217	Mean dependent var	0.059927
Adjusted R-squared	0.010014	S.D. dependent var	1.071256
S.E. of regression	1.065878	Akaike info criterion	2.562621
Sum squared resid	2931.129	Schwarz criterion	2.589751
Log likelihood	-3309.157	Hannan-Quinn criter.	2.572452
F-statistic	3.382729	Durbin-Watson stat	1.031794
Prob(F-statistic)	0.000115		

Appendix 9-3a: Estimation results of the GARCH (1,1) For 2000-2004

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:36
Sample: 1/03/2000 12/31/2004
Included observations: 1130
Convergence achieved after 20 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.085714	0.026397	3.247134	0.0012
M3	-0.274539	0.087527	-3.136617	0.0017
M7	-0.320212	0.075956	-4.215739	0.0000
Y03	0.156406	0.055516	2.817322	0.0048
Variance Equation				
C	0.251525	0.049820	5.048667	0.0000
RESID(-1)^2	0.500164	0.096463	5.185010	0.0000
GARCH(-1)	0.346724	0.072706	4.768870	0.0000
T-DIST. DOF	4.437882	0.582040	7.624697	0.0000

R-squared	0.006314	Mean dependent var	0.134090
Adjusted R-squared	0.000114	S.D. dependent var	1.038751
S.E. of regression	1.038692	Akaike info criterion	2.548606
Sum squared resid	1210.505	Schwarz criterion	2.584216
Log likelihood	-1431.962	Hannan-Quinn criter.	2.562060
F-statistic	1.018437	Durbin-Watson stat	1.299142
Prob(F-statistic)	0.416256		

Appendix 9-3b: Estimation results of the EGARCH (1,1) For 2000-2004

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:40
Sample: 1/03/2000 12/31/2004
Included observations: 1130
Convergence achieved after 14 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(5) + C(6)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(7)
*RESID(-1)/@SQRT(GARCH(-1)) + C(8)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.097721	0.024742	3.949533	0.0001
M3	-0.258199	0.086686	-2.978546	0.0029
M7	-0.307250	0.070947	-4.330725	0.0000
Y03	0.143367	0.053950	2.657422	0.0079
		Variance Equation		
C(5)	-0.469377	0.051901	-9.043671	0.0000
C(6)	0.592464	0.073442	8.067146	0.0000
C(7)	0.103590	0.039754	2.605760	0.0092
C(8)	0.798696	0.041585	19.20637	0.0000
T-DIST. DOF	4.643048	0.659161	7.043879	0.0000

R-squared	0.007828	Mean dependent var	0.134090
Adjusted R-squared	0.000747	S.D. dependent var	1.038751
S.E. of regression	1.038363	Akaike info criterion	2.544449
Sum squared resid	1208.660	Schwarz criterion	2.584511
Log likelihood	-1428.614	Hannan-Quinn criter.	2.559585
F-statistic	1.105554	Durbin-Watson stat	1.301209
Prob(F-statistic)	0.356556		

Appendix 9-3c: Estimation results of the GARCH-M (1,1) for 2000-2004

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:43
Sample: 1/03/2000 12/31/2004
Included observations: 1130
Convergence achieved after 21 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.168790	0.096217	1.754260	0.0794
C	-0.060932	0.082757	-0.736270	0.4616
M3	-0.285714	0.087721	-3.257063	0.0011
M7	-0.311443	0.075462	-4.127164	0.0000
Y03	0.157116	0.055850	2.813186	0.0049
Variance Equation				
C	0.257469	0.050480	5.100417	0.0000
RESID(-1)^2	0.493704	0.096647	5.108339	0.0000
GARCH(-1)	0.346460	0.072636	4.769791	0.0000
T-DIST. DOF	4.345173	0.563579	7.709968	0.0000

R-squared	0.012205	Mean dependent var	0.134090
Adjusted R-squared	0.005156	S.D. dependent var	1.038751
S.E. of regression	1.036070	Akaike info criterion	2.547190
Sum squared resid	1203.328	Schwarz criterion	2.587252
Log likelihood	-1430.162	Hannan-Quinn criter.	2.562326
F-statistic	1.731417	Durbin-Watson stat	1.291045
Prob(F-statistic)	0.087040		

Appendix 9-3d: Estimation results of the GJR-GARCH (1,1) for 2000-2004

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:44
Sample: 1/03/2000 12/31/2004
Included observations: 1130
Convergence achieved after 21 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0) + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.088934	0.026196	3.394937	0.0007
M3	-0.270596	0.086637	-3.123334	0.0018
M7	-0.319470	0.074030	-4.315381	0.0000
Y03	0.153671	0.055625	2.762632	0.0057
		Variance Equation		
C	0.224962	0.044405	5.066135	0.0000
RESID(-1)^2	0.618858	0.129577	4.775995	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.287620	0.125645	-2.289153	0.0221
GARCH(-1)	0.383681	0.068871	5.570993	0.0000
T-DIST. DOF	4.544508	0.623231	7.291851	0.0000

R-squared	0.006715	Mean dependent var	0.134090
Adjusted R-squared	-0.000374	S.D. dependent var	1.038751
S.E. of regression	1.038946	Akaike info criterion	2.544303
Sum squared resid	1210.016	Schwarz criterion	2.584364
Log likelihood	-1428.531	Hannan-Quinn criter.	2.559438
F-statistic	0.947299	Durbin-Watson stat	1.299681
Prob(F-statistic)	0.476243		

Appendix 9-3e: Estimation results of the PGARCH (1,1) for 2000-2004

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:46
Sample: 1/03/2000 12/31/2004
Included observations: 1130
Convergence achieved after 30 iterations
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(9) = C(5) + C(6)*(ABS(RESID(-1)) - C(7)*RESID(
-1))^C(9) + C(8)*@SQRT(GARCH(-1))^C(9)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.089231	0.026105	3.418133	0.0006
M3	-0.266901	0.086642	-3.080497	0.0021
M7	-0.315747	0.073916	-4.271702	0.0000
Y03	0.152638	0.055518	2.749321	0.0060
		Variance Equation		
C(5)	0.217917	0.045489	4.790510	0.0000
C(6)	0.437706	0.081736	5.355143	0.0000
C(7)	-0.163704	0.066727	-2.453323	0.0142
C(8)	0.427590	0.075759	5.644099	0.0000
C(9)	1.754202	0.459054	3.821337	0.0001
T-DIST. DOF	4.565576	0.629397	7.253893	0.0000

R-squared	0.006833	Mean dependent var	0.134090
Adjusted R-squared	-0.001148	S.D. dependent var	1.038751
S.E. of regression	1.039348	Akaike info criterion	2.546011
Sum squared resid	1209.873	Schwarz criterion	2.590525
Log likelihood	-1428.496	Hannan-Quinn criter.	2.562829
F-statistic	0.856125	Durbin-Watson stat	1.299861
Prob(F-statistic)	0.564362		

Appendix 9-4a: Estimation results of the GARCH (1,1) for 2005-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 22:57
Sample: 1 1462
Included observations: 1462
Convergence achieved after 16 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(9) + C(10)*RESID(-1)^2 + C(11)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.271686	0.048583	-5.592219	0.0000
M9	-0.202293	0.072563	-2.787832	0.0053
M10	-0.158630	0.066101	-2.399806	0.0164
Y05	0.273526	0.065119	4.200390	0.0000
Y06	0.324712	0.062111	5.227935	0.0000
Y07	0.427875	0.063723	6.714589	0.0000
Y09	0.146547	0.074769	1.959997	0.0500
Y10	0.282707	0.066186	4.271423	0.0000
Variance Equation				
C	0.096713	0.015115	6.398532	0.0000
RESID(-1)^2	0.520204	0.068390	7.606465	0.0000
GARCH(-1)	0.471885	0.039506	11.94454	0.0000
T-DIST. DOF	8.354632	1.488242	5.613759	0.0000

R-squared	0.018620	Mean dependent var	0.002606
Adjusted R-squared	0.011175	S.D. dependent var	1.092626
S.E. of regression	1.086504	Akaike info criterion	2.555555
Sum squared resid	1711.712	Schwarz criterion	2.598955
Log likelihood	-1856.111	Hannan-Quinn criter.	2.571744
F-statistic	2.500963	Durbin-Watson stat	0.842250
Prob(F-statistic)	0.004085		

Appendix 9-4b: Estimation results of the EGARCH (1,1) For 2005-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:00
Sample: 1 1462
Included observations: 1462
Convergence achieved after 26 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(11) + C(12)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(13)*RESID(-1)/@SQRT(GARCH(-1)) + C(14)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.274511	0.047143	-5.822992	0.0000
M8	-0.191112	0.078977	-2.419829	0.0155
M9	-0.193798	0.060915	-3.181447	0.0015
M10	-0.164827	0.060026	-2.745935	0.0060
M11	-0.126411	0.066663	-1.896282	0.0579
Y05	0.296056	0.061769	4.792973	0.0000
Y06	0.320282	0.056950	5.623878	0.0000
Y07	0.448704	0.060240	7.448553	0.0000
Y09	0.192347	0.073407	2.620286	0.0088
Y10	0.305859	0.061785	4.950393	0.0000
		Variance Equation		
C(11)	-0.576150	0.046203	-12.46993	0.0000
C(12)	0.701976	0.065046	10.79197	0.0000
C(13)	0.050572	0.033419	1.513250	0.1302
C(14)	0.844882	0.022840	36.99170	0.0000
T-DIST. DOF	8.360380	1.495371	5.590839	0.0000

R-squared	0.019298	Mean dependent var	0.002606
Adjusted R-squared	0.009809	S.D. dependent var	1.092626
S.E. of regression	1.087254	Akaike info criterion	2.563111
Sum squared resid	1710.528	Schwarz criterion	2.617361
Log likelihood	-1858.634	Hannan-Quinn criter.	2.583347
F-statistic	2.033829	Durbin-Watson stat	0.842801
Prob(F-statistic)	0.012923		

Appendix 9-4c: Estimation results of the GARCH-M (1,1) for 2005-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:04
Sample: 1 1462
Included observations: 1462
Convergence achieved after 25 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(11) + C(12)*RESID(-1)^2 + C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.274702	0.062994	4.360780	0.0000
C	-0.463720	0.064490	-7.190566	0.0000
M8	-0.224655	0.066284	-3.389281	0.0007
M9	-0.229818	0.069418	-3.310653	0.0009
M10	-0.168287	0.066733	-2.521808	0.0117
M11	-0.139579	0.065291	-2.137813	0.0325
Y05	0.296401	0.058926	5.030037	0.0000
Y06	0.350028	0.055956	6.255444	0.0000
Y07	0.434559	0.056526	7.687751	0.0000
Y10	0.294298	0.058932	4.993897	0.0000
	Variance Equation			
C	0.087222	0.014440	6.040394	0.0000
RESID(-1)^2	0.472490	0.062104	7.608027	0.0000
GARCH(-1)	0.512772	0.037944	13.51403	0.0000
T-DIST. DOF	8.514013	1.575526	5.403919	0.0000

R-squared	0.026153	Mean dependent var	0.002606
Adjusted R-squared	0.017410	S.D. dependent var	1.092626
S.E. of regression	1.083073	Akaike info criterion	2.547153
Sum squared resid	1698.572	Schwarz criterion	2.597786
Log likelihood	-1847.969	Hannan-Quinn criter.	2.566040
F-statistic	2.991274	Durbin-Watson stat	0.849952
Prob(F-statistic)	0.000239		

Appendix 9-4d: Estimation results of the GJR-GARCH (1, 1) for 2005-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:05
Sample: 1 1462
Included observations: 1462
Convergence achieved after 19 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*RESID(-1)^2*(RESID(-1)<0)
+ C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.205669	0.039773	-5.171031	0.0000
M8	-0.120782	0.068900	-1.753009	0.0796
M9	-0.232459	0.073743	-3.152283	0.0016
M10	-0.166902	0.067956	-2.456033	0.0140
M11	-0.061032	0.063905	-0.955043	0.3396
Y05	0.221818	0.058660	3.781390	0.0002
Y06	0.267561	0.055250	4.842715	0.0000
Y07	0.373933	0.057125	6.545929	0.0000
Y10	0.244771	0.059055	4.144762	0.0000
		Variance Equation		
C	0.097899	0.015243	6.422384	0.0000
RESID(-1)^2	0.529701	0.080147	6.609087	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.062640	0.086231	-0.726424	0.4676
GARCH(-1)	0.482163	0.039709	12.14240	0.0000
T-DIST. DOF	8.322875	1.517219	5.485612	0.0000

R-squared	0.019499	Mean dependent var	0.002606
Adjusted R-squared	0.010696	S.D. dependent var	1.092626
S.E. of regression	1.086767	Akaike info criterion	2.557990
Sum squared resid	1710.178	Schwarz criterion	2.608623
Log likelihood	-1855.890	Hannan-Quinn criter.	2.576877
F-statistic	2.215096	Durbin-Watson stat	0.842845
Prob(F-statistic)	0.007404		

Appendix 9-4e: Estimation results of the PGARCH (1, 1) for 2005-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:06
Sample: 1 1462
Included observations: 1462
Convergence achieved after 24 iterations
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(14) = C(10) + C(11)*(ABS(RESID(-1)) - C(12)*RESID(
-1))^C(14) + C(13)*@SQRT(GARCH(-1))^C(14)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.203750	0.039848	-5.113195	0.0000
M8	-0.117748	0.068906	-1.708816	0.0875
M9	-0.231342	0.074137	-3.120480	0.0018
M10	-0.167278	0.067723	-2.470031	0.0135
M11	-0.060725	0.063915	-0.950095	0.3421
Y05	0.219320	0.058751	3.733024	0.0002
Y06	0.265037	0.055195	4.801860	0.0000
Y07	0.372764	0.057111	6.527040	0.0000
Y10	0.241588	0.059112	4.086941	0.0000
		Variance Equation		
C(10)	0.100755	0.022106	4.557830	0.0000
C(11)	0.492933	0.073978	6.663197	0.0000
C(12)	-0.032347	0.044398	-0.728585	0.4663
C(13)	0.488207	0.051141	9.546336	0.0000
C(14)	1.916322	0.418158	4.582775	0.0000
T-DIST. DOF	8.337569	1.517691	5.493587	0.0000

R-squared	0.019566	Mean dependent var	0.002606
Adjusted R-squared	0.010080	S.D. dependent var	1.092626
S.E. of regression	1.087105	Akaike info criterion	2.559324
Sum squared resid	1710.062	Schwarz criterion	2.613574
Log likelihood	-1855.866	Hannan-Quinn criter.	2.579560
F-statistic	2.062600	Durbin-Watson stat	0.842906
Prob(F-statistic)	0.011434		

Appendix 9-5a: Estimation results of the GARCH (1, 1) for 2005 July 2007

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:11
Sample: 1/04/2005 7/31/2007
Included observations: 621
Convergence achieved after 16 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.040846	0.034202	1.194234	0.2324
D5	0.166515	0.054898	3.033186	0.0024
Y05	-0.088562	0.050542	-1.752239	0.0797
		Variance Equation		
C	0.071737	0.020505	3.498529	0.0005
RESID(-1)^2	0.376733	0.082130	4.587060	0.0000
GARCH(-1)	0.538095	0.070961	7.582967	0.0000
T-DIST. DOF	8.536674	2.535317	3.367103	0.0008

R-squared	0.003425	Mean dependent var	0.128687
Adjusted R-squared	-0.006313	S.D. dependent var	0.838967
S.E. of regression	0.841612	Akaike info criterion	2.076091
Sum squared resid	434.9025	Schwarz criterion	2.126042
Log likelihood	-637.6263	Hannan-Quinn criter.	2.095506
F-statistic	0.351711	Durbin-Watson stat	0.955050
Prob(F-statistic)	0.908969		

Appendix 9-5b: Estimation results of the EGARCH (1,1) for 2005-July 2007

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:13
Sample: 1/04/2005 7/31/2007
Included observations: 621
Convergence achieved after 16 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8)
*RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.163868	0.056030	2.924632	0.0034
D5	0.159012	0.051587	3.082407	0.0021
M8	0.299001	0.112203	2.664823	0.0077
Y05	-0.230330	0.067109	-3.432206	0.0006
Y06	-0.149811	0.063111	-2.373760	0.0176
Variance Equation				
C(6)	-0.510874	0.074449	-6.862057	0.0000
C(7)	0.533339	0.083210	6.409531	0.0000
C(8)	0.098988	0.045727	2.164772	0.0304
C(9)	0.857806	0.035218	24.35724	0.0000
T-DIST. DOF	8.599547	2.632600	3.266560	0.0011

R-squared	0.036742	Mean dependent var	0.128687
Adjusted R-squared	0.022553	S.D. dependent var	0.838967
S.E. of regression	0.829453	Akaike info criterion	2.075162
Sum squared resid	420.3632	Schwarz criterion	2.146520
Log likelihood	-634.3377	Hannan-Quinn criter.	2.102897
F-statistic	2.589494	Durbin-Watson stat	0.988172
Prob(F-statistic)	0.006191		

Appendix 9-5c: Estimation results of the GARCH-M (1,1) for 2005 July-2007

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:26
Sample: 1/04/2005 7/31/2007
Included observations: 621
Convergence achieved after 14 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.249954	0.123221	2.028492	0.0425
C	-0.153111	0.073743	-2.076259	0.0379
D5	0.163786	0.053800	3.044352	0.0023
M8	0.173566	0.106612	1.628011	0.1035
		Variance Equation		
C	0.069528	0.019873	3.498567	0.0005
RESID(-1)^2	0.389547	0.079538	4.897654	0.0000
GARCH(-1)	0.535101	0.067264	7.955260	0.0000
T-DIST. DOF	8.395949	2.536900	3.309531	0.0009

R-squared	0.015019	Mean dependent var	0.128687
Adjusted R-squared	0.003771	S.D. dependent var	0.838967
S.E. of regression	0.837384	Akaike info criterion	2.072188
Sum squared resid	429.8431	Schwarz criterion	2.129274
Log likelihood	-635.4144	Hannan-Quinn criter.	2.094376
F-statistic	1.335262	Durbin-Watson stat	0.971313
Prob(F-statistic)	0.230889		

Appendix 9-5d: Estimation results of the GJR-GARCH (1,1) for 2005 July-2007

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:28
Sample: 1/04/2005 7/31/2007
Included observations: 621
Convergence achieved after 16 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0) + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.048231	0.034081	1.415183	0.1570
D5	0.172223	0.054314	3.170887	0.0015
M8	0.252170	0.104948	2.402824	0.0163
Y05	-0.111236	0.050972	-2.182285	0.0291
	Variance Equation			
C	0.074764	0.020095	3.720563	0.0002
RESID(-1)^2	0.483817	0.115076	4.204329	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.225428	0.115031	-1.959711	0.0500
GARCH(-1)	0.528444	0.068732	7.688483	0.0000
T-DIST. DOF	8.568715	2.608605	3.284789	0.0010

R-squared	0.022089	Mean dependent var	0.128687
Adjusted R-squared	0.009306	S.D. dependent var	0.838967
S.E. of regression	0.835054	Akaike info criterion	2.067793
Sum squared resid	426.7574	Schwarz criterion	2.132015
Log likelihood	-633.0497	Hannan-Quinn criter.	2.092755
F-statistic	1.728018	Durbin-Watson stat	0.974649
Prob(F-statistic)	0.088880		

Appendix 9-5e: Estimation results of the PGARCH (1,1) for 2005 July 2007

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:29
Sample: 1/04/2005 7/31/2007
Included observations: 621
Convergence achieved after 25 iterations
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(8) = C(4) + C(5)*(ABS(RESID(-1)) - C(6)*RESID(-1))^C(8) + C(7)*@SQRT(GARCH(-1))^C(8)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.043184	0.034528	1.250700	0.2110
D5	0.175159	0.054884	3.191451	0.0014
Y05	-0.083633	0.049868	-1.677085	0.0935
		Variance Equation		
C(4)	0.045015	0.035666	1.262127	0.2069
C(5)	0.372020	0.102390	3.633347	0.0003
C(6)	-0.127609	0.071003	-1.797227	0.0723
C(7)	0.449080	0.120785	3.718027	0.0002
C(8)	2.974644	1.346245	2.209586	0.0271
T-DIST. DOF	8.421702	2.551717	3.300406	0.0010

R-squared	0.004423	Mean dependent var	0.128687
Adjusted R-squared	-0.008591	S.D. dependent var	0.838967
S.E. of regression	0.842564	Akaike info criterion	2.072281
Sum squared resid	434.4671	Schwarz criterion	2.136503
Log likelihood	-634.4432	Hannan-Quinn criter.	2.097243
F-statistic	0.339843	Durbin-Watson stat	0.956782
Prob(F-statistic)	0.950359		

Appendix 9-6a: Estimation results of the GARCH (1,1) For August 2007-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:33
Sample: 1 841
Included observations: 841
Convergence achieved after 17 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.177058	0.055461	-3.192462	0.0014
M6	-0.283767	0.128625	-2.206160	0.0274
M8	-0.571994	0.088251	-6.481433	0.0000
M9	-0.433140	0.092888	-4.663030	0.0000
M10	-0.338559	0.100237	-3.377601	0.0007
M12	-0.161516	0.093702	-1.723708	0.0848
Y07	0.513411	0.092603	5.544185	0.0000
Y09	0.146967	0.080407	1.827801	0.0676
Y10	0.320496	0.069866	4.587277	0.0000
	Variance Equation			
C	0.157295	0.029381	5.353679	0.0000
RESID(-1)^2	0.612565	0.107557	5.695259	0.0000
GARCH(-1)	0.392056	0.050786	7.719813	0.0000
T-DIST. DOF	8.347618	2.151893	3.879198	0.0001

R-squared	0.023003	Mean dependent var	-0.090493
Adjusted R-squared	0.008843	S.D. dependent var	1.239542
S.E. of regression	1.234049	Akaike info criterion	2.874484
Sum squared resid	1260.941	Schwarz criterion	2.947671
Log likelihood	-1195.721	Hannan-Quinn criter.	2.902533
F-statistic	1.624568	Durbin-Watson stat	0.815781
Prob(F-statistic)	0.079655		

Appendix 9-6b: Estimation results of the EGARCH (1,1) For August 2007-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:34
Sample: 1 841
Included observations: 841
Convergence achieved after 31 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(10) + C(11)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(12)*RESID(-1)/@SQRT(GARCH(-1)) + C(13)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.189398	0.053993	-3.507852	0.0005
M6	-0.373857	0.122638	-3.048464	0.0023
M8	-0.613167	0.088320	-6.942546	0.0000
M9	-0.444732	0.076728	-5.796183	0.0000
M10	-0.336329	0.085289	-3.943418	0.0001
M12	-0.229931	0.086652	-2.653497	0.0080
Y07	0.580488	0.080836	7.181101	0.0000
Y09	0.210951	0.076866	2.744394	0.0061
Y10	0.352315	0.063882	5.515111	0.0000
	Variance Equation			
C(10)	-0.700506	0.066198	-10.58204	0.0000
C(11)	0.918231	0.102998	8.915019	0.0000
C(12)	0.034710	0.057478	0.603884	0.5459
C(13)	0.745451	0.041453	17.98285	0.0000
T-DIST. DOF	8.638430	1.992840	4.334734	0.0000

R-squared	0.020862	Mean dependent var	-0.090493
Adjusted R-squared	0.005470	S.D. dependent var	1.239542
S.E. of regression	1.236147	Akaike info criterion	2.872028
Sum squared resid	1263.705	Schwarz criterion	2.950844
Log likelihood	-1193.688	Hannan-Quinn criter.	2.902234
F-statistic	1.355398	Durbin-Watson stat	0.814837
Prob(F-statistic)	0.175337		

Appendix 9-6c: Estimation results of the GARCH-M (1,1) For August 2007 to 2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:36
Sample: 1 841
Included observations: 841
Convergence achieved after 20 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(9) + C(10)*RESID(-1)^2 + C(11)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.256274	0.079214	3.235224	0.0012
C	-0.409256	0.085062	-4.811250	0.0000
M6	-0.344111	0.124647	-2.760678	0.0058
M8	-0.591388	0.081580	-7.249199	0.0000
M9	-0.378623	0.092767	-4.081422	0.0000
M10	-0.265983	0.100670	-2.642118	0.0082
Y07	0.474492	0.087617	5.415500	0.0000
Y10	0.316978	0.062502	5.071523	0.0000
		Variance Equation		
C	0.161541	0.030532	5.290897	0.0000
RESID(-1)^2	0.578108	0.103301	5.596369	0.0000
GARCH(-1)	0.404050	0.052905	7.637253	0.0000
T-DIST. DOF	8.639435	2.313094	3.735013	0.0002

R-squared	0.026313	Mean dependent var	-0.090493
Adjusted R-squared	0.013393	S.D. dependent var	1.239542
S.E. of regression	1.231213	Akaike info criterion	2.865371
Sum squared resid	1256.670	Schwarz criterion	2.932928
Log likelihood	-1192.889	Hannan-Quinn criter.	2.891262
F-statistic	2.036596	Durbin-Watson stat	0.818015
Prob(F-statistic)	0.022689		

Appendix 9-6d: Estimation results of the GJR-GARCH (1,1) For August 2007 to 2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 07/02/12 Time: 21:36
Sample: 1 841
Included observations: 841
Convergence achieved after 28 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*RESID(-1)^2*(RESID(-1)<0)
+ C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.177079	0.056467	-3.135998	0.0017
M6	-0.283795	0.128645	-2.206029	0.0274
M8	-0.571778	0.088322	-6.473801	0.0000
M9	-0.433128	0.092943	-4.660166	0.0000
M10	-0.338566	0.100268	-3.376615	0.0007
M12	-0.161363	0.093699	-1.722148	0.0850
Y07	0.513183	0.092852	5.526890	0.0000
Y09	0.146854	0.080440	1.825635	0.0679
Y10	0.320158	0.069916	4.579160	0.0000
	Variance Equation			
C	0.157411	0.029412	5.351899	0.0000
RESID(-1)^2	0.609836	0.121904	5.002597	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.006545	0.140470	0.046595	0.9628
GARCH(-1)	0.391736	0.050947	7.689109	0.0000
T-DIST. DOF	8.344753	2.151557	3.878472	0.0001

R-squared	0.022995	Mean dependent var	-0.090493
Adjusted R-squared	0.007637	S.D. dependent var	1.239542
S.E. of regression	1.234800	Akaike info criterion	2.876859
Sum squared resid	1260.952	Schwarz criterion	2.955675
Log likelihood	-1195.719	Hannan-Quinn criter.	2.907065
F-statistic	1.497242	Durbin-Watson stat	0.815773
Prob(F-statistic)	0.112182		

Appendix 9-6e: Estimation results of the PGARCH (1,1) For August 2007-2010

Dependent Variable: RETURN
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/21/12 Time: 23:40
Sample: 1 841
Included observations: 841
Convergence achieved after 52 iterations
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(15) = C(11) + C(12)*(ABS(RESID(-1)) - C(13)*RESID(
-1))^C(15) + C(14)*@SQRT(GARCH(-1))^C(15)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.160155	0.058146	-2.754368	0.0059
M3	-0.138280	0.103978	-1.329894	0.1836
M5	0.125875	0.128239	0.981564	0.3263
M8	-0.591249	0.088306	-6.695462	0.0000
M9	-0.429933	0.081647	-5.265759	0.0000
M10	-0.336416	0.092264	-3.646236	0.0003
M12	-0.203913	0.087646	-2.326548	0.0200
Y07	0.522158	0.082848	6.302611	0.0000
Y09	0.170258	0.076335	2.230389	0.0257
Y10	0.303704	0.065623	4.628000	0.0000
	Variance Equation			
C(11)	0.179264	0.032910	5.447040	0.0000
C(12)	0.517531	0.097418	5.312500	0.0000
C(13)	0.004734	0.064859	0.072984	0.9418
C(14)	0.451453	0.057266	7.883442	0.0000
C(15)	1.192402	0.348992	3.416703	0.0006
T-DIST. DOF	8.660635	2.095532	4.132906	0.0000

R-squared	0.024693	Mean dependent var	-0.090493
Adjusted R-squared	0.006961	S.D. dependent var	1.239542
S.E. of regression	1.235220	Akaike info criterion	2.879409
Sum squared resid	1258.759	Schwarz criterion	2.969484
Log likelihood	-1194.791	Hannan-Quinn criter.	2.913930
F-statistic	1.392523	Durbin-Watson stat	0.815923
Prob(F-statistic)	0.143684		

Appendix 9-7: GARCH Model Specification and performance Characteristics for the study periods

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
Overall 2000-2010	GARCH(1,1)	September, 2000 2008, 2009	0.1485	0.5322	0.4265	-	-	Reliable, Persistent volatility, $\alpha+\beta=0.9587$, strong impact of current and old news on volatility, no asymmetric effects, persistent volatility	2.5651	2.5854	2.575	-3315.342	
	EGARCH(1,1)	2008, 2009	-0.5284	0.6604	0.8249 < 1	0.00	0.00		2.5704	2.5885	2.5770	-3323.258	
	GARCH-M(1,1)	September,2000, 2008, 2009	0.1484	0.5248	0.4313	0.00	0.00	$\alpha+\beta=0.9561$ Same results as with GARCH (1,1) but slightly less volatility persistence	2.5620	2.5847	2.5702	-3310.413	GARCH-M(1,1) model

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
	GJR-GARCH(1,1)	September 2008, 2009	0.1475	0.5937	0.4319	-0.1545		$\alpha+\beta+\gamma/2 = 0.9484 < 1$; model reliable with highly persistent volatility	2.5658	2.5861	2.5731	-3316.243	
	PGARCH(1,1)	September, 2000, 2003, 2008, 2009	0.1529	0.4767	0.4723			$\alpha+\beta = 0.9490 < 1$; model reliable with persistent volatility; good impact of new and old information on volatility	2.5626	2.5896	2.5725	-3309.157	

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
Pre-reforms 2000-2004	GARCH(1,1)	March, July, 2003	0.2515	0.5001	0.3467			$\alpha + \beta = 0.8468$ < 1, so model is reliable; strong impact of old and new information on volatility; volatility fairly persistent but much less so than post-reform models	2.5486	2.5842	2.5621	-1431.962	
	EGARCH(1,1)	March, July, 2003	-0.4694	0.5925	0.7987 < 1	0.00	0.00	Model is reliable with no leverage or asymmetric effects	2.5444	2.5845	2.5596	-1426.614	

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
	GARCH-M(1,1)	March, July, 2003	0.2575	0.4937	0.3465	0.00	0.00	$\alpha+\beta=0.8402$ < 1 Model reliable; no symmetric effect; fairly persistent volatility	2.5472	2.5873	2.5623	-1430.162	
	GJR-GARCH(1,1)	March, July, 2003	0.2250	0.6189	0.3837	-0.2876 significant asymmetric effect (p = 0.0221)		$\alpha+\beta+\gamma/2=$ 0.8588 < 1; model reliable; fairly persistent volatility; strong impact of current and old news on volatility	2.5443	2.5844	2.5594	-1428.531	GJR-GARCH(1, 1) model
	PGARCH(1,1)	March, July, 2003	0.2179	0.4377	0.4276			$\alpha+\beta=0.8653$ < 1; same results as overall period but weaker volatility persistence; no	2.5460	2.5905	2.5628	-1428.496	

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
								symmetric effect					
Post-reforms 2005-2010	GARCH(1,1)	September ,October, 2005, 2006, 2007, 2009, 2010	0.0967	0.5202	0.4719			$\alpha + \beta = 0.9921$ < 1; model reliable with far more persistent volatility than for the pre-reform period	2.5556	2.5989	2.5717	-1856.111	
	EGARCH(1,1)	August, September, October 2005, 2006, 2007, 2010	-0.5762	0.7020	0.8449 < 1	0.00	0.00	Model reliable; no asymmetric volatility effect due to bad news; persistent volatility; clear evidence of more vigorous volatility effects with more significant factors	2.5631	2.6174	2.5833	-1858.634	

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
	GARCH-M(1,1)	August, September, October, November, 2005, 2006, 2007, 2010	0.0822	0.4725	0.5128	0.00	0.00	$\alpha+\beta=0.9853$ < 1; model is reliable; far more persistent volatility than for pre-reform period; no asymmetric effect;	2.5447	2.6423	2.5811	-1833.156	GARCH-M(1,1) model
	GJR-GARCH(1,1)	September, October, 2005, 2006, 2007, 2010	0.0979	0.5297	0.4822	-0.0626		$\alpha+\beta+\gamma/2=$ 0.9809 <1; model is reliable; strong impact of old and new information on volatility; insignificant asymmetric effect ($p = 0.4676 >> 0.05$)	2.5580	2.6086	2.5769	-1855.890	
	PGARCH(1,1)	September, 2005, 2006, 2007, 2010	0.1008	0.4929	0.4882			$\alpha+\beta=0.9811$ < 1; model reliable; strong impact of old and new	2.5593	2.6136	2.5796	-1855.866	

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
								information; very strong volatility persistence; no asymmetric effect					
Post-reforms-Pre-crisis 2005-July2007	GARCH(1,1)	Friday, 2005	0.0717	0.3767	0.5381			$\alpha+\beta=0.9148$ < 1; ditto; slightly weaker volatility persistence than above	2.0761	2.1260	2.0955	-637.6263	
	EGARCH(1,1)	Friday, August, 2005, 2006	-0.5109	0.5333	0.8578 < 1	0.00	0.00	Model reliable; high impact of old and new information, but much more for new information; no asymmetric effects	2.0752	2.1465	2.1029	-634.3377	
	GARCH-M(1,1)	Friday	0.0695	0.3895	0.5351			$\alpha+\beta=0.9246$ < 1; ditto for GARCH(1,1) model	2.0722	2.1293	2.0943	-635.4144	

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
	GJR-GARCH(1,1)	Friday, August, 2005,	0.0747	0.4838	0.5284	-0.2254		$\alpha+\beta+\gamma/2=$ 0.8995 < 1; model is reliable; strong impact of old and new information on volatility; but much lower volatility persistence than previous models; significant asymmetric effect (p = 0.0500 = 0.05)	2.0678	2.1320	2.0928	-633.0497	GJR-GARCH(1, 1) model
	PGARCH(1,1)	Friday	0.0450	0.3720	0.4491			$\alpha+\beta=0.8211$ < 1; model reliable; strong impact of new and old information; fairly persistent volatility	2.0723	2.1365	2.0972	-634.4432	

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
Post-reforms-Post-crisis August 2007-2010	GARCH(1,1)	June, August, September, October, 2007, 2010	0.1573	0.6126	0.3921			$\alpha+\beta=1.0047>$ 1; model unreliable; more volatility effects manifested	2.8745	3.9477	2.9025	-1195.721	
	EGARCH(1,1)	June, August, September, October, December, 2007, 2009, 2010	-0.7005	0.9182	0.7455 <1	0.00	0.00	Model reliable; more volatility effects manifested	2.8702	2.9508	2.9022	-1193.688	
	GARCH-M(1,1)	June, August, September, October, 2007, 2010	0.1615	0.5781	0.4041			$\alpha+\beta=0.9822<$ 1; so model a bit unreliable but fully integrated and reliable; persistent volatility; no symmetric effect	2.8654	2.9329	2.8913	-1192.889	GARCH-M(1,1) model

Details / Periods	Model	Significant return variables	Model Parameters					Model Interpretation	Performance Criterion				Model Contest
			ω	α	β	γ	δ		AIC	SC	HQ	LOG-L	
	GJR-GARCH(1,1)	June, August, September, October, December, 2007, 2010	0.1574	0.6098	0.3917	0.0065		$\alpha+\beta+\gamma/2=$ 1.0048 > 1; model unreliable; strong impact of old and new information on volatility; persistent volatility; insignificant asymmetric effect (p = 0.9843 >> 0.05)	2.8769	2.9557	2.9071	-1195.719	
	PGARCH(1,1)	August, September, October, December, 2007, 2009, 2010	0.1793	0.5175	0.4515			$\alpha+\beta=0.9690<$ 1; ditto for same model in preceding period; but more volatility persistence; more impact of old versus new information	2.8794	2.9695	2.9139	-1194.791	