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A multifactor asset pricing model of the natural resource sector in Africa

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Declaration

I hereby declare that this research is my own work and has not been copied in part or whole from any other source. Where relevant sources were used, due acknowledgement was accorded. I conducted this research under the guidance of my director of studies, Dr Timothy Rodgers.

Dedication

To Ezenwa Tony-Okeke and Jachimike Tony-Okeke

Acknowledgement

For the grace to complete this work, I give thanks to God. I am indebted to my wife, Adaugo; my parents, Dr and Dr (Mrs) A. I. Okeke; my siblings, Obinna and Ezinne; and my friend Tunde, for their care and love throughout the course of this research. I am grateful to my supervisory team for their invaluable support and to my colleagues at Coventry University for their best wishes. I am also indebted to my extended family and to my friends, for their contributions.

Abstract

The importance of the African market has increased in the past few years thanks to the continent's fast-growing economies. However, research on asset pricing within the market remains very low. This study comprehensively investigates asset pricing within the resource sector of the African equity market.

To achieve a robust analysis, data problems within the African market had to be addressed. To do this, I formed indices of African markets; this was done by the creation of two major indices – the emerging African market index and the frontier African market index. A further two indices were created – the South African market index and the emerging African market excluding South Africa index. I also employ this classification because I expect differences in the results within these markets.

One major problem identified in the literature review regarding previous research in the African market is the lack of adjustments for survivorship bias. In analysing survivorship bias, I used the Jensen alpha approach and the mean difference approach, which identified survivorship bias of 297.47 basis points per week and 359.00 basis points per week for the emerging African market, using each approach respectively.

In analysing the performance of asset-pricing models within the African continent, I find significant differences across all four market indices, due to the varying levels of *integration* with world markets. I find that beta is consistently positive and significant, however, while size and liquidity are both significant but their direction depends on the characteristics of the surveyed market. I also find that value and momentum factors have a positive relationship with returns, but their importance depends on the level of integration with world markets.

The coskewness measure was found to be important only in the frontier African market, while the cokurtosis measure is important in an emerging African market context (including when South Africa is excluded). For the contagion factor, there seems to be an offsetting effect between the dummy and higher-order moments in the emerging African market; otherwise, contagion is negative and significant.

This contagion factor accounts for the financial crisis and the Arab Spring. This offered a unique opportunity to test the impact of contagion on unconditional, as well as conditional, asset-pricing models.

In analysing the conditional model, I employed GARCH-type models and found beta in the frontier African market to be unstable, while the high alpha parameter values in the South African market, the emerging African market and the emerging African market excluding South Africa showed no significance.

In testing for contagion using the conditional beta, I employed the dummy variable test and the comparison-of-means test; both showed evidence of *contagion* within the emerging African index, the emerging African index excluding South Africa and the frontier African market index. There was no evidence of contagion within the South African market and I attribute this to the *interdependence* between the South African market and Western markets.

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Acronyms and Abbreviations

ADCC	Asymmetric dynamic conditional correlation
AIC	Akaike information criterion
AIG	American International Group
AIMS	Alternative Investment Market Segment
AR	Auto regression
ARCH	Autoregressive conditional heteroscedasticity
ARFIMA	Autoregressive fractionally integrated moving averages
ASES	African Stock Exchanges Association
B/M	Book-to-market value
BDS	Brock, Dechert and Scheinkman
BEKK	Baba, Engle, Kraft and Kroner
BRVM	Bourse Regionale des Valeurs Mobilieres SA
BSE	Botswana Stock Exchange
BSM	Botswana share market
CAPM	Capital asset pricing model
CASE	Cairo Alexandria Stock Exchange
CBOE	Chicago Board Options Exchange
CDSC	Central Depository and Settlement Corporation Limited
CPI	Consumer price index
CRSP	Centre for Research in Security Prices
CSD	Central Securities Depository
CUSUM	Cumulative sum control chart
DASS	Delivery and settlement system
DC	Domestic companies

DCC	Dynamic conditional correlation
EGX	Egyptian Exchange
FDI	Foreign direct investment
FHFA	Federal Housing Finance Agency
FIGARCH	Fractionally integrated GARCH
FISMS	Fixed Income Securities Market segment
FOMC	Federal Open Market Committee
FTSE	Financial Times Stock Exchange
G30	Group of Thirty
GARCH	Generalised autoregressive conditional heteroscedasticity
GDP	Gross domestic product
GJR-GARCH	Glosten, Jagannathan and Runkle - generalised autoregressive conditional heteroscedasticity
GMM	Generalised methods of moments
GSE	Government sponsored enterprise
HAC	Heteroscedasticity and autocorrelation consistent
HFR	Hedge Fund Research, Inc
HML	High minus low
HQ	Hannan-Quinn criterion
ICAPM	International capital asset pricing model
ICB	Industrial classification benchmark
IDR	Issuer default rating
IID	Independent and identically distributed
IMF	International Monetary Fund
IMR	Inverse mills ratio

IMV	Illiquid minus very liquid
IOSCO	International Organisation of Securities Commission
ISA	Investments and Securities Act
JSE	Johannesburg Stock Exchange
MAROCLEAR	Maroclear Depositaire Central des Valeurs Mobilieres
MBS	Mortgaged backed securities
MCL	Monte Carlo likelihood
MCMC	Monte Carlo Markov chain
MENA	Middle East and North Africa
MIMS	Main Investment Market Segment
MKT	Market
MPC	Monetary policy committee
MS	Markov switching
MSCI	Morgan Stanley Capital International
MSM	Markov switching market
NASI	NSE All Share Index
NEPAD	New African Partnership for Development
NGSEOILG5	NSE Oil & Gas index
NSE	Nigerian Stock Exchange
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary least squares
PACF	Partial autocorrelation function
RIC	Reuters Instrument Code
SA	South Africa

SAD	Seasonal affective disorder
SAE	Societe Anonyme Egyptienne
SAFICAS	Southern African Financial Instruments Clearing and Settlement System
SC	Schwarz criterion
SE	Stock exchange
SEC	Securities and Exchange Commission
SETS	Settlements
SMB	Small minus big
SV	Stochastic volatility
TARP	Troubled asset relief programme
TPM	Transition probability matrix
TRBC	Thomson Reuters Business Classification
TUNINDEX	Tunisia Stock Exchange
UMD	Up minus down
UMEAO	Union Monétaire et économique de l'Afrique de l'Ouest
US3MT	US 3-months Treasury bill
VIX	Volatility index
WAEMU	West African Economic and Monetary Union
WML	Winner minus loser

1 INTRODUCTION

1.1 Background

Asset-pricing studies have developed enormously following the seminal works of Sharpe (1964) and Lintner (1965). Some of the important examinations of the CAPM include the works of Miller and Scholes (1972), Merton (1973), Roll (1977), Fama and French (1992, 1993), Carhart (1997), Hwang and Satchell (1999) and Pástor and Stambaugh (2003). The results of these studies have not remained uncontested, with a number of papers offering a rebuttal of some of the findings while others support them.

Most of these studies have, however, been carried out in the developed markets and the emerging markets in Asia and Latin America, with limited asset pricing research in the African market. This is due to the relative newness of the market, thin trading and problems of illiquidity; however, these have improved drastically in the past 10–15 years. We are now beginning to see some research into the African market, such as those in Omran (2007), Hearn and Piesse (2009) and Alagidede (2011). However, the pace still remains slow.

African stock markets have become increasingly important thanks to their fast-growing economies. According to Assefa and Mollick (2014), there has been a remarkable increase in the total value of stocks traded in the African stock markets (in dollar terms) of more than 1,700% on average from 1995 to 2010. In terms of absolute returns and risk-adjusted returns, the African stock market performed very well, with an average annual return of 25% between 2000 and 2010. With the exception of 2008, there has been a very significant increase in performance with some markets achieving returns of more than 100% in some years, as seen in Malawi and Egypt.

According to Alagidede (2011), average returns on African stocks reached 44% in 2004, as compared to 36% in Japan (Nikkei), 26% in the US and 32% in Europe (Standard and Poor's) and 30% on the Morgan Stanley Capital International (MSCI) index. Although the average return was 44% in 2004, there were some spectacular returns within individual markets in US dollar terms – Zimbabwe (30%), Egypt (67%), Ghana (70%) and Kenya (75%). A year later, the Nigerian stock market and Cote d'Ivoire posted a 100% increase in the value of stocks in dollar terms.[1] Harvey (1995) comments on the benefits of portfolio diversification given these

[1] Alagidede P. (2011). Return behaviour in Africa's emerging equity markets. *The Quarterly Review of Economics and Finance*, 51, 133–140.

returns in the African market and also with returns being uncorrelated with developed market returns. Alagidede (2011) also identifies zero correlation (and sometimes negative correlation) of African markets with developed markets.

As highlighted in Hearn and Piesse (2009), the importance of this market is expected to rise even further, with the current drive towards integration being pursued by regional bodies such as the African Stock Exchanges Association (ASES) and the New African Partnership for Development (NEPAD). There is, however, a wide variety of markets at very different levels of development, from the fledgling markets of Botswana and Zambia to the largest and most developed market in South Africa. This results from a considerable contrast in levels of regulation and regulatory enforcement.

This difference in levels of development within the African market and between the African markets and world markets raises some doubt about the viability of the application of asset-pricing models developed mainly in developed markets. In emerging markets, the importance of the most prominent risk factors of beta, size and book-to-market value remain mixed, as identified in Lischewski and Voronkova (2012). Even studies in the developed markets have sometimes identified results contradictory to other studies, as seen in Reinganum (1981), Stambaugh (1982) and Lakonishok and Shapiro (1986) and Fama and French (1992, 1993).

1.2 The motivation and statement of the problem

Within the African market, there is yet to be a consensus asset-pricing model, as most studies have focused on parts of the market or analysed the importance of some variables and not others; as seen in Appiah-Kusi and Menyah (2003), Mecagni and Sourial (1999), Smith and Jerreris (2005), Omran (2007) and Alagidede (2011). This mostly results from the paucity of data in some African countries in the past, although more recently some data have become available for most of the markets with a stock exchange. It has thus become an important research endeavour to examine asset pricing in Africa's stock markets with a more wholisic approach, as this knowledge will be invaluable to professional fund managers, academic researchers and regulators. This is the gap this thesis seeks to fill.

The peculiarity of the African market, however, will possibly make the optimal asset pricing model different, when compared to expectation in the developed markets. This is because stock markets in Africa remain small in terms of market capitalisation when compared with developed markets. As stated above, Lischewski and Voronkova (2012) have identified that the importance of the most prominent risk factors of beta, size and book-to-market value remains mixed in the emerging markets; the expectation is also varied within the African market. The evaluation of the importance of these factors in the African market is important as studies in the past have not been able to use the Fama–French factors. This is because they have not been available for most the markets, as shown in Cheng et al. (2010)

Beyond these three factors, identified initially by Fama and French (1992, 1993), the characteristics of the African market may give credence to other factors. For example, the severe illiquidity in the African market as identified in Allen, Otchere and Senbet (2011) may have an impact on the determinants of asset pricing.

In investigating the four-factor model, Carhart (1997) employed the momentum as defined in Jegadeesh and Titman (1993) within developed markets. Given the informational efficiency of the African market, as highlighted in Ntim (2012), momentum may be an even more important factor within the African market. Also, most studies in the developing and emerging markets find contradictory evidence. However, given the relative newness of the African market, the importance of momentum in the African market is still not clear-cut. Researchers such as Rouwenhorst (1999) even argue that it is quite difficult to detect momentum in emerging markets. The importance of momentum will hence be explored in this thesis.

An even rarer concept within asset pricing is the impact of contagion on estimates of asset-pricing models. As highlighted in Pettenuzzo and Timmermann (2011), investors face parameter uncertainty and uncertainty as to the function form of the true process, along with model instability risk, which are breaks in the parameters of the returns-generating process. Contagion has become an important factor since the 2008 global recession; given the spread of the crisis from the US to other countries due to the international linkages of financial systems. According to Morales and Andreosso-O'Callaghan (2014), the question that springs to mind is whether the severity of the impact of the financial crisis on different world economies is directly related to the level of integration of financial markets. Morales and Andreosso-O'Callaghan (2014) posed a question which also relates to African market in particular – are all economies of the world affected in the same way? This question was asked because different financial systems are at different levels of development.

During periods of financial crisis, shocks in one stock market can be transmitted among world equity markets, as in contagion. But the main question is to which extent contagion affects returns variation in affected markets. The events that will be analysed within this study are those that may induce structural breaks and create contagion from other markets. This is where the original event does not occur in the African market identified but originates from developed or other emerging markets. These will be analysed within asset-pricing models to highlight any potential impact of contagion on returns variation.

Before the formation of asset portfolios to be used in asset pricing tests, one problem that needs to be eliminated is that of survivorship bias. According to Rohleder et al. (2011) and many more in the literature, survivorship generally biases returns upwards. This overestimation of performance results from the fact that the predominant rationale for firm disappearance is poor performance, as highlighted in Malkiel (1995). This is particularly important as most asset pricing research within the African market does not control for survivorship bias. Given this finding, this study will not only eliminate survivorship bias from the dataset but will also model the behaviour of survivorship bias in the emerging African market index. Studies in developed markets have found a strong relationship between survivorship bias and attrition rate; this study will also investigate this relationship in the African market.

The final discussion for this study centres around the instability in beta. As stated in Jagannathan and Wang (1996), the constant beta assumption of the static CAPM is not reasonable as the relative risk of an asset is likely to vary over time. They insist that beta and expected return will, in general, depend on the nature of the information available at any given point in time and vary over time as information set changes. During periods of bad economic conditions, for example, the expected market risk premium is relatively high, more leveraged firms are likely to face more financial difficulties and have higher conditional betas, but the static CAPM seldom accounts for this. Lusting and Van Neiuwerburgh (2005) and Santos and Veronesi (2006) find beta to be time-varying within their sample.

This is expected to be particularly important in the African market given that the African market remains relatively illiquid and with problems of thin trading; which will make it susceptible to shocks as identified in Mlambo and Biekpe (2003). The relatively weak economic environment as highlighted in Kenny and Moss (1998) does not help ensure that beta is stable either. Following this indication, this study will test time variation in beta using a GARCH-type model.

1.2.1 Research aims, objectives and hypothesis

Chapter 2 provides justification for the research objectives identified here; these have been identified in the context of the existing literature on asset pricing in the African continent. The research objectives are summarised as follows.

Survivorship bias: The aim is to evaluate the impact of survivorship bias on asset-pricing models in the emerging African market. The objective is to evaluate the *magnitude of survivorship bias* in the emerging African market using two methods – *Rohleder, Scholz and Wilkens (2011), and Eling (2008).*

Structural break: The aim is to analyse the potential impact of structural breaks on the asset-pricing models, while the objective is to analyse potential *changes in the structure of data* in the markets that make up the emerging and frontier Africa indices using the Bai and Perron (1998, 2003) methodology. The second objective is to identify the breaks in the returns index using the Chow (1960) test.

Models: There are considerable differences between the economic/social structures within individual countries in the African continent, which means it is very unlikely that there is a "one size fits all" asset-pricing model I can develop for Africa as a whole. In this thesis, the objective will, therefore, be to identify differences in the asset pricing models for the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market. This fits into the aim, which is to identify which of the *alternative unconditional factor models* is most appropriate for explaining realised returns in each of the sampled indices.

Factor loading: The aim is to assess *the important factors* in each of the sampled indices. The objective is to determine the significance and directions of the factors examined. The factors examined are beta, size, book-to-market value, momentum, liquidity and higher moments (coskewness and cokurtosis).

Conditional CAPM: The aim here is to examine *time variation in beta*. The objective is to identify if beta within the sampled indices relates to conditional information, using the DCC/ADCC GARCH model.

Contagion: The aim is to identify the impact of contagion on the behaviour of asset-pricing models within the indices sampled. The objective is to examine the *potential impact of contagion* on the estimates of conditional beta.

The research hypothesis relates to the optimal model in the markets investigated, the importance of different factors, the impact of contagion, the impact of conditional information, the explanatory power of higher order moments and the nature of survivorship bias. These are developed in Section 2.12 within the literature review.

1.3 Novel contributions of the thesis

The thesis makes the following contribution to the asset-pricing literature in the African market.

The thesis makes a contribution to the African CAPM literature by taking into consideration the impact of survivorship bias on the modelling of stock-market returns. To the best of my knowledge, this has not been undertaken comprehensively before in the emerging African market context.

Grinblatt and Titman (1989) were among the first to identify in a US context that failure to take survivorship bias into consideration would bias the econometric modelling of stock returns. The findings in my thesis indicate that this issue is even more important in an African context.

Attrition rates are directly related to survivorship bias; a low attrition rate will lead to low survivorship bias, as identified in Liang (2000). This study finds the average attrition rate in the emerging African market to be much higher than those found in US studies, therefore calling into question previous studies on asset pricing in African markets that do not adjust for survivorship bias.

The thesis identifies the factors that determine returns on stocks in one of the key economic sectors on the continent; namely the natural resources (basic materials) sector. The standard three-factor Fama-French model is extended in an African context to include additional issues relating to momentum, liquidity, third- and fourth-moment effects, and also contagion effects (financial and political). The model explores differences between the South African

market, emerging African market and frontier African market and discusses the comparative results.

The thesis finds significant differences in the factors that determine returns across the South African, emerging and frontier African markets, which highlights the tendency for the determinants to change with the degree of integration with Western markets, although with significant peculiarities on the direction of some of the variables within the African market.

The thesis also explores the impact of African market volatility on the market beta in a time-varying context. This is undertaken using a DCC/ADCC-based GARCH (and GJR) methodology. It also focuses on identifying the impact of financial and political contagion events on the market beta during the period considered.

The thesis finds a significant time-varying effect on the frontier African market, but the high parameter value in the South African market, the emerging African market and the emerging African market excluding South Africa was insignificant. Contagion resulting from the financial and political crisis had a significant impact of the conditional beta within the emerging African market, the emerging African market excluding South Africa and the frontier African markets, but not the South African market because of its interdependence with Western markets.

1.4 Significance of the study and general philosophy.

The general philosophy described here relates to the overall progression of the research and how the various parts are related. The philosophy of science approach for this thesis, as it relates to major theoretical contributions of *Karl Popper*, *Thomas Kuhn* and *Imre Lakatos*, is discussed in the methodology section.

The performance of the Sharpe-Lintner CAPM has been questioned, as identified earlier; Chapter 2, Section 2.2 provides an overview of the CAPM, identifying tests that dispute and some that affirm the validity of the CAPM. With all the questions around its validity, however, it remains universally in use by practitioners. Within this study, I take the premise that the CAPM can be applied within the African market, but also recognise that it may not be the optimal asset-pricing model given the unique characteristics of these markets. Therefore, I investigate various alternative models and highlight the most optimal, identifying the rationales and implications.

To investigate the factors that are important in the African equity market, the study identifies several methodologies that can be applied. However, to make sure this thesis is comprehensive, the standard Sharpe-Lintner CAPM is applied along with the Fama-French three-factor model and the Carhart four-factor model. To account for the impact of illiquidity and investors' preference for positive skewness and aversion to high kurtosis, the four-factor model is augmented by the liquidity factor and the coskewness and cokurtosis factors. This thesis also accounts for the impact of contagion on the performance of the asset-pricing models.

The need to account for liquidity is exacerbated by the very low number of listed companies in the African market when compared with companies listed in developed markets. For example, Senbet and Otchere (2010) identify that five companies constitute 75% of the transactions in Abidjan while Ashanti Goldfields represents 90% of the total capitalisation of the Ghana stock market. The number of these companies has also fluctuated considerably as identified in Allen, Otchere and Senbet (2011). The thin nature of these markets makes them susceptible to increased volatility following large orders of traders.

To address this problem along with problems of sparse trading identified in Ekechi (1989), Bowie (1994) and Mlambo et al. (2003), I have formed the emerging and frontier market regional indices following the FTSE quality of market criteria (AFRICA) of March 2014 (Chapter 3, Sections 3.2 and 3.3). To address the sample selection problems, which the study finds to be a major problem (Chapter 4), I use the Centre for Research in Security Prices (CRSP) methodology to eliminate survivorship bias in the sample.

In accounting for the effect of higher moments, I accommodate criticisms of the traditional mean-variance approach, which suggests that the behaviour of stock market returns is departing from the frequently assumed normal distribution as documented in Hwang and Satchell (1999) and Harvey and Siddiqui (1999, 2000). In considering contagion, I take the premise that contagion (from the 2008 financial crisis and the Arab Spring) had an impact on the returns-generating process within the sample.

This stems from the fact that during financial crisis in other parts of the world, investors have a tendency to reassess fundamentals, which in itself increases the probability of the crisis spreading to other regions. This describes the "wake-up call" theory of contagion as identified in Ahnert and Bertsch (2014) (Chapter 2, Section 2.6). To identify the contagion period, this thesis uses the actual timeline as identified in the chapter appendix in Section 3.11 of Chapter 3. In the case of the 2008 financial crisis, confirmation is achieved by using the CBOE volatility index (VIX).

Because of the criticisms of the unconditional CAPM (Chapter 2, Section 2.8) and to further investigate the impact of time variation, this thesis employs the dynamic conditional correlation (DCC) analysis of Engle (2002) and also the asymmetric dynamic conditional correlation in the multivariate GARCH (1, 1), GARCH (2, 1) and GJR-GARCH models (rationale is provided in Chapter 7). Initially, a dummy variable is used to test for contagion in conditional correlation (Chapter 7, Section 7.2.5), while the robustness check takes the form of a comparison-of-means test (Chapter 7, Section 7.2.6). Other potential alternative methods – threshold CAPM, Kalman filters, stochastic volatility and Markov switching approach –are also discussed in Section 3.8.6 of Chapter 3.

1.5 Data and scope of the thesis

The scale of the literature on asset pricing is vast, with a large number of potential tests of the CAPM, using competing methodologies. It is, therefore, essential to identify the exact scope of this thesis. The scope of the research is as follows.

The research shall focus on the African equity market, using the FTSE quality of market criteria (AFRICA) of March 2014, which classified the African market into the emerging African market and the frontier African market. The thesis limits the sample to this classification. They classified South Africa as an advanced emerging market, while Egypt and Morocco were classified as emerging markets and, for the purpose of this research, South Africa, Egypt and Morocco were classified as emerging African market. The following countries were classified as frontier markets: Botswana, Cote d'Ivoire, Ghana, Kenya, Mauritius, Nigeria and Tunisia. Due to the paucity of data in Ghana and Mauritius, both markets are excluded from the analysis. Based on these classifications, I form two principal indices: the emerging African market index and the frontier African market index. These indices are formed to alleviate data problems in regard to the frequency of data and survivorship bias; it also provides diversification benefits (see Section 3.3 in Chapter 3 for detailed justification).

Because of the size of the South African market relative to the rest of Africa, two further indices are formed: the South African market index and the emerging African market excluding South

Africa index. This is to ensure that the characteristics of the emerging African market index are not blurred by the South African market and, in the case of the South African market index, to help highlight the possible impact of integration with world markets. It is also expected that different factors will influence the returns across these indices.

The population for this study is limited to the natural resources sector (basic materials indices). This is because the resource sector drives the economies within the African continent and makes up a large percentage of the market capitalisation within the countries' markets. To a large extent, this sector drives other sectors within the economy of the African countries and hence can be a good gauge of broader economic performance. For example, and as seen in Chapter 3, Section 3.2, basic materials make up 26% of the Johannesburg Stock Exchange. Resource-driven stocks in Egypt and Morocco from about 38.4% and 15.3% of the total market capitalisation, respectively.

The survivorship bias elimination technique is limited to the CRSP methodology (as justified in Chapter 3, Section 3.4). To demonstrate the magnitude of survivorship bias in the African market, I devote a whole chapter (Chapter 4) to highlight this and its potential impact on portfolio returns and asset pricing studies in the African continent. It is paramount to eliminate survivorship bias due to its tendency to bias returns upward and distort CAPM estimates. This is also very essential given the high attrition rate identified in Chapter 4.

It is important to note that the aim of this chapter is only to highlight this problem and its potential impact, hence I use only the emerging African market and, for robustness, the South African market, along with a shorter sample period (2005–2014). This is warranted following the rather surprising finding that most asset pricing studies in this continent do not address this problem, even giving the obvious implications on estimates of asset-pricing models.

The scope of the methodology is quite exhaustive as I consider the Sharpe-Lintner CAPM, the Fama-French three-factor model, the Carhart four-factor model and the liquidity, higher-moments augmented models, and also include a contagion dummy. In analysing the momentum factor, the discussion chapter (Chapter 8) employs the behavioural finance literature. The literature is also evaluated in Chapter 2, Section 2.2.6. Beyond this, the analysis does not employ any more behavioural finance literature, but this will be an important area for further studies. As identified earlier, I also employ the DCC/ADCC GARCH model as I consider it sufficient for the analysis required, and I also identify other potential alternatives that could be employed.

Before the application of the DCC/ADCC GARCH models, structural break tests are carried out to identify potential breaks in the structure of the series. These tests are performed on the market indices of each country within the sample before the formation of the market portfolio. The motivation is to ensure that possible breaks are identified and taken into account, as the formation of the index can blur the identification of breaks. I also carry out structural break tests to identify further breaks after the formation of the regional market portfolios, using the index returns.

Although I find a relatively large number of breaks across the markets studied (Chapter 3, Section 3.8.4.2), I account for these only within the DCC/ADCC GARCH model and further specify the 2008 financial crisis and the Arab Spring political crisis for the contagion test.

Literature-supported steps are followed in the formation of the market, size, value, momentum and liquidity portfolios, and the coskewness and cokurtosis measures in the emerging Africa market, the emerging Africa market excluding South Africa, the frontier Africa market and the South Africa market samples. The details of the steps, modifications applied and rationale are detailed in Chapter 3, Section 3.9.1.

I observe that the research on the impact of contagion within the African market remains sparse with largely no research on the impact of the 1990s crisis on returns behaviour in the African market, except the South Africa market. This is obviously different when compared with developed markets.

This was possibly a result of the relative underdevelopment of other African markets at the time or a reflection of the low level of correlation between the African market and developed markets. However, with the development and growing importance of the African market, the linkage between the developed markets and the African markets is becoming stronger. This makes accounting for contagion in asset pricing absolutely essential.

1.6 Structure of the thesis

The thesis has the following structure

Introduction (Chapter 1): The introduction provides some context for asset-pricing research in the African market and also gives some perspective on the evolution of the market. It also identifies the scope of the research, the research objectives and the novel contributions of the thesis.

Literature review (Chapter 2): The review provides a historical perspective of the CAPM along with its shortfalls, highlighting potential implications for an African CAPM. This chapter forms the foundation for the discussions in subsequent chapters.

This chapter has the objective of highlighting the issues around the CAPM, especially in regards to peculiar characteristics of the African market. It evaluates the theoretical and empirical foundations of the application of asset-pricing models and identifies gaps in existing studies within the African market.

Data description, index creation, methodological notes and portfolio formation (Chapter 3): The methods to be applied within the thesis mostly depend on the structure of the data, hence this chapter evaluates the data in the emerging and frontier African markets.

The objective of this chapter is to describe the structure of the data available, explain the index creation procedure and the subsequent methodological approach applied.

Survivorship bias (Chapter 4): This chapter highlights the magnitude and impact of survivorship bias on estimates of asset-pricing models, following the Jensen alpha methodology of Rohleder, Scholz and Wilkens (2011), and the mean difference methodology identified in Eling (2008).

The objective of this chapter is to highlight the significant problem of survivorship bias in the emerging African market and, for robustness, the South African market only.

Empirical results (Chapter 5): This chapter evaluates the results in the South African market, the emerging African market (and also the emerging African market excluding South Africa) and the frontier African market.

The objective of this chapter is to provide a detailed analysis of the results within each index, highlighting the best performing model and the importance (and direction) of each factor.

Comparative discussion of results (Chapter 6): This chapter discusses the findings identified in Chapter 5 above, but with the view of understanding how important factors change as markets become more mature.

The objective of this chapter is to analyse how market characteristics affect the results-expectation, as the African markets evolve from being frontier markets to being emerging markets.

Conditional CAPM (Chapter 7): This chapter applies the dynamic conditional correlation (and asymmetric dynamic conditional correlation) analysis based on GARCH (1, 1), GARCH (2, 1) and GJR-GARCH. To test for the impact of contagion on unconditional beta, this chapter applies a dummy variable test for the crisis period (financial crisis and the Arab Spring) and uses an equality-of-means test for robustness.

The objective is to analyse the structure of the conditional beta and the impact of contagion on estimates of conditional beta in the markets surveyed.

Conclusion and areas for further research (Chapter 8): The chapter provides a summary of the major findings and novel contribution of the thesis. It also identifies the potential implications of the findings to various stakeholders and areas of further research within the African market.

The objective of this chapter is to summarise the thesis, highlight the main findings, summarise the implications of the findings to various stakeholders and identify possible directions for further development of the research.

1.7 Background/overview of the African market

The stock market in Africa remains the smallest of any region despite the surge in the establishment of stock exchanges, particularly in Sub-Saharan Africa, in the last two decades. These stock exchanges still face serious challenges in terms of market capitalisation and listing, except the two oldest markets in South Africa and Egypt, established in the 1880s. However, as stated in Alagidede (2011) the mean market capitalisation (as a percentage of GDP) for each of the sub-regions has been increasing steadily. But as of 2008, the market capitalisation of Egypt has decreased by 50% while that of South Africa dropped by 40%. The mean number of companies listed in Africa has also been decreasing and stood at 92 in 2009, as opposed to 129 in 2007.

Conventionally, a market is liquid if it can absorb trades without large changes in price, as defined in Allen and Gale (1994). When markets are thin, volatility increases along with the tendency for asset prices to react adversely to the orders of traders, as stated in Pagano (1989). In measuring liquidity in the African market, Allen, Otchere and Senbet (2011) employed two measures. The first measures the market's trading activity, relative to the size of the economy, by the total value of shares traded on the exchange scaled by the GDP. The second measure uses the turnover ratio based on the total value of shares traded relative to market capitalisation.

Figure 1.1 Market capitalisation of listed companies (% of GDP) (source: Allen, Otchere and Senbet, 2011, p4)

Market capitalization of listed companies (% of GDP).

Region	Country	Market capitalization as a percent of GDP								Number of listed domestic companies						
		2003	2004	2005	2006	2007	2008	2009	Country	2003	2004	2005	2006	2007	2008	2009
Eastern Africa	Kenya	28	24	34	51	50	32	36	Kenya	51	47	47	51	51	53	55
	Tanzania	7	6	4	4	–	6	–	Tanzania	6	6	6	6	7	7	–
	Uganda	1	1	1.12	1.17	–	–	–	Uganda	3	5	5	5	–	6	8
	Average	12	10	13	19	50	19	36	Subtotal	20	19	19	21	29	22	32
Northern Africa	Egypt	33	49	89	87	107	53	48	Egypt	967	792	744	603	435	373	305
	Morocco	26	44	46	75	101	76	69	Morocco	53	52	56	65	74	77	78
	Tunisia	10	9	10	14	15	16	23	Tunisia	46	44	46	48	50	49	49
	Average	23	34	48	59	74	49	47	Subtotal	355	296	284	239	186	166	144
Southern Africa	Botswana	26	26	23	36	48	27	34	Botswana	19	18	18	18	18	19	20
	Malawi	4	6	8	19	–	42	–	Malawi	40	41	42	41	90	41	–
	Mauritius	37	39	41	56	83	40	55	Mauritius	8	8	9	10	9	14	88
	Namibia	6	7	6	7	8	7	9	Namibia	13	13	13	9	9	7	7
	South Africa	161	211	233	277	294	178	246	South Africa	426	403	388	401	422	425	363
	Swaziland	10	10	8	7	7	–	–	Swaziland	5	6	6	6	6	7	5
	Zambia	17	8	14	11	21	–	–	Zambia	12	13	15	14	15	–	–
	Zimbabwe	67	41	70	–	–	–	–	Zimbabwe	81	79	79	80	82	81	94
	Average	41	44	50	59	77	59	86	Subtotal	76	73	71	72	81	85	96
Western Africa	Cote d'Ivoire	12	13	14	24	42	30	20	Cote d'Ivoire	38	39	39	40	38	38	38
	Ghana	19	30	16	25	16	21	16	Ghana	25	29	30	32	32	35	35
	Nigeria	14	16	17	22	52	23	20	Nigeria	200	207	214	202	212	213	214
	Average	15	20	16	24	37	25	21	Subtotal	88	92	94	91	95	95	96

Figure 1.2 Liquidity of African markets (source: Allen, Otchere and Senbet, 2011, p6)

Liquidity of African stock markets.

Panel A: stocks traded, total value (% of GDP)

Region	Country	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Eastern Africa	Kenya	0.81	0.56	0.57	0.37	0.31	0.28	1.40	2.14	2.69	5.78	4.89	4.17	1.65
	Tanzania	–	0.00	0.08	0.44	0.08	0.19	0.19	0.15	0.10	0.08	–	–	–
	Uganda	–	–	–	–	0.00	0.01	0.00	0.00	0.03	0.06	–	–	–
	Average	0.81	0.28	0.33	0.41	0.13	0.16	0.53	0.76	0.94	1.97	4.89	4.17	1.65
Northern Africa	Egypt	7.47	5.93	9.96	11.14	3.99	2.91	3.95	7.11	28.31	44.16	40.68	42.77	28.04
	Morocco	3.14	3.47	6.37	2.95	2.58	1.45	1.39	2.95	6.97	20.57	34.98	25.40	32.38
	Tunisia	1.38	0.95	2.02	3.22	1.58	1.05	0.66	0.80	1.57	1.69	1.86	3.72	3.18
	Average	3.99	3.45	6.12	5.77	2.72	1.80	2.00	3.62	12.28	22.14	25.84	23.96	21.20
Southern Africa	Botswana	1.14	1.35	0.67	0.77	1.08	0.93	1.05	0.51	0.43	0.66	0.89	1.11	0.89
	Mauritius	–	–	–	–	–	–	0.34	0.24	0.28	0.45	–	1.40	3.83
	Malawi	3.08	2.44	1.80	1.69	2.46	1.25	1.89	1.57	2.40	2.14	5.44	4.66	–
	Namibia	0.66	0.38	0.66	0.56	0.22	0.04	0.03	0.27	0.09	0.23	0.26	0.22	0.24
	South Africa	30.05	43.45	54.75	58.32	58.81	71.10	61.69	75.38	82.67	121.23	150.05	145.07	119.76
	Swaziland	0.01	0.01	0.01	0.02	0.77	0.02	0.00	0.00	0.00	0.00	–	–	–
	Zambia	0.20	0.08	0.38	0.25	1.46	0.05	0.25	0.12	0.20	0.21	0.63	–	–
	Zimbabwe	6.40	3.07	3.80	3.77	14.91	11.35	18.18	2.88	9.70	–	–	–	–
	Average	5.93	7.25	8.87	9.34	11.39	12.11	10.43	10.12	11.97	17.85	31.45	30.49	31.18
Western Africa	Cote d'Ivoire	0.20	0.31	0.68	0.32	0.08	0.14	0.18	0.30	0.19	0.62	0.80	1.35	0.58
	Ghana	0.71	0.80	0.32	0.20	0.25	0.18	0.60	0.74	0.63	0.41	0.73	0.93	0.37
	Nigeria	0.36	0.50	0.42	0.57	1.03	0.80	1.27	1.90	1.73	2.42	10.11	9.41	2.71
	Average	0.43	0.54	0.47	0.36	0.45	0.38	0.68	0.98	0.85	1.15	3.88	3.89	1.22

Panel B: stocks traded, turnover ratio (%)

Region	Country	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Eastern Africa	Kenya	0.28	0.28	0.31	3.58	3.40	3.79	7.41	8.15	9.83	14.63	10.60	11.83	4.59
	Tanzania	–	–	3.40	–	2.40	1.85	–	–	2.29	2.10	–	–	–
	Uganda	–	–	–	–	–	–	–	–	3.13	5.22	–	–	–
	Average	0.28	0.28	1.86	3.58	2.90	2.82	7.41	8.15	5.08	7.32	10.60	11.83	4.59
Northern Africa	Egypt, Arab Rep.	53.26	22.28	31.61	34.74	14.20	16.13	13.73	17.31	42.97	54.82	45.60	61.85	60.07
	Morocco	10.20	10.08	17.60	9.22	10.00	10.65	6.45	9.10	15.86	35.26	42.10	31.05	45.73
	Tunisia	1.44	0.89	13.25	23.29	12.60	13.73	7.16	9.16	16.50	14.26	13.30	25.48	16.23
	Average	21.63	11.08	20.82	22.42	12.27	13.50	9.11	11.86	25.11	34.78	33.67	39.46	40.68
Southern Africa	Botswana	0.61	1.13	0.71	4.78	5.60	5.04	4.36	2.30	1.81	2.27	2.20	3.05	2.74
	Mauritius	–	–	–	–	–	13.84	–	–	–	3.49	–	3.92	8.06
	Malawi	3.81	2.86	2.65	5.01	9.30	11.51	6.22	4.45	6.05	4.42	8.00	8.85	–
	Namibia	4.10	2.30	0.60	4.51	3.00	5.18	0.74	4.82	1.50	3.78	3.70	2.84	3.03
	South Africa	29.43	30.38	34.13	33.90	37.40	78.86	44.80	47.37	39.32	48.80	55.00	60.61	57.27
	Swaziland	126.00	–	0.20	–	9.80	6.68	0.03	–	0.01	0.03	–	–	–
	Zambia	2.00	–	4.70	–	20.80	22.47	–	–	1.99	2.11	4.10	–	–
	Zimbabwe	17.10	9.24	12.04	10.77	29.40	19.19	26.14	9.22	15.27	6.19	5.10	–	–
	Average	26.15	9.18	7.86	11.79	16.47	20.35	13.71	13.63	9.42	8.89	13.02	15.86	17.77
Western Africa	Cote d'Ivoire	2.20	4.50	10.81	2.59	0.70	0.72	1.61	2.66	1.41	3.30	2.50	4.08	2.01
	Ghana	5.82	6.49	3.35	1.48	2.60	2.47	4.12	3.24	2.24	2.14	3.90	5.19	1.96
	Nigeria	5.48	5.20	5.07	7.29	10.20	10.65	10.99	13.73	11.46	13.64	28.20	29.30	11.01
	Average	4.50	5.40	6.41	3.79	4.50	4.61	5.57	6.54	5.04	6.36	11.53	12.86	4.99

From Figure 1.2, it's clear that stock markets in Africa are thin and illiquid with the exception of Egypt and South Africa. In some cases, as in the case of East African markets, liquidity is terribly low with stocks traded being less than 1% of GDP. Sometimes, very few companies dominate the market in some of these African countries, for example, according to Senbet and Otchere (2010), five companies constitute 75% of the transactions in Abidjan while Ashanti Goldfields represents 90% of the total capitalisation of the Ghana stock market. Allen et al. (2009) unsurprisingly found that when liquidity in African markets is compared with other regions, even in comparison with other developing countries, it still looks abysmal.

Others who recognise the acute illiquidity in African markets include Kenny and Moss (1998), who highlight that the small size, illiquidity and often unstable economic and political environments of African markets make them extremely volatile. Examples of this volatility, in Kenny and Moss (1998), can be seen in Zimbabwe's stock exchange index, with gains of 133% and 110% in 1990 and 1993, respectively, but reporting losses in 1991 and 1992 of −55% and −59%, respectively.

The problems of illiquidity and thin trading have been widely researched as acknowledged in Dimson (1979), Cohen et al. (1983), Lo and MacKinlay (1990), Miller, Muthuswamy and Whaley (1994) and Bowie (1994). The bias caused by thin trading in the serial correlation of index returns was first identified by Fisher (1966). He points out that this bias results in recorded prices not being necessarily equal to their underlying theoretical values. This results in discrepancies between the indices from these share prices and the underlying values of the shares. Lo and MacKinlay (1990b) also highlights that econometric problems are bound to arise when one ignores the fact that the statistical behaviour of sampled data may be quite different from the behaviour of the underlying stochastic process from which the sample was obtained. Pagano (1989) develops a model that captures the relationship between market thinness and volatility; he finds that market thinness leads to more volatility irrespective of the volatility of the asset fundamentals.

Using a sample of the 20 most actively traded stocks on the Nigeria stock exchange between 1980 and 1986, Ekechi (1989) found that for the whole period covered, none of the stocks was traded every single day, with the most active stock traded on 509 of the 1,512 trading days for the period. Bowie (1994) found that out of 10 trading days, thinly traded stocks did not trade more than eight days. He used daily data of 367 securities listed on the Johannesburg Stock Exchange. Using daily data between 1997 and 2002, Mlambo et al. (2003) found that eight out of 35 socks on Morocco's Casablanca Stock Exchange, 10 out of 40 stocks on Kenya's Nairobi Stock Exchange, nine out of 63 stocks on the Egyptian Stock Exchange and eight out of 39 stocks on the Zimbabwe Stock Exchange did not trade on more than 75% of the respective trading days.

Biekpe and Mlambo (2005) found that thin trading is a problem in the African stock market. They also identified that at some specific time period within their sample, investors who intend to benefit from short-term price fluctuations may not find them favourable. They, however, identify that serial correlation induced by thin trading is only minimal in individual stock returns. This, they say, raises doubt where previous studies used index data without adjustments for thin trading within the African stock market.

Many more authors document the well-known empirical finding that thin markets are more volatile in comparison to thick markets. These authors include Tauchen and Pitts (1983).

Beyond illiquidity and thin trading, Ntim (2012) finds that despite the rapid development in establishment of stock markets in Africa, with the exception of South Africa, stock markets in Africa remain small in terms of market capitalisation and also small compared to the size of their economies, as also identified in Ntim et al (2011). Ntim (2012) also highlights the vulnerability of African stocks to speculation and manipulation by insiders, due to their small size. This results from the level of allocative, operational and, in particular, informational efficiency within the African market. This is also supported by the findings of Smith et al (2002).

Irving (2005) hence identifies the importance of regional integration and corporation in deepening the financial market. According to Ntim (2012), this will lead to a larger stock market with a robust regulatory, monitoring and enforcement framework that should be less vulnerable to speculation and manipulation. The use of better communications and technological infrastructure can minimise operational costs, thereby improving overall market efficiency, as stated in Ntim (2011). This can be achieved by the reduction of duplication and the improvement of information flow into the market.

1.6.1 The emerging African market index

The constituents of the emerging African market index are South Africa, Egypt and Morocco.[2]

1.6.1.1 South Africa

The oldest and largest market in Africa remains the Johannesburg Stock Exchange (JSE). Established in 1887, the JSE adopted a sophisticated electronic trading system following the end of the outcry system in 1996. The JSE uses the Southern African Financial Instruments Clearing and Settlement System (SAFICAS) as its central depository, and it is based on technology employed in the Swiss stock exchange. The levels of corporate governance are quite high following the King I and II reports[3] and international regulatory standards.[4] According to Hearn et al. (2010), the South African stock market is the best-regulated market in Africa.

The JSE represents one of the most developed stock markets in Africa, and it also has the highest market capitalisation within Africa as reported in Yartey (2008). Within the JSE, the mining stocks remain the best known; however, according to PageReyaneke (1997), the growth of the commercial and industrial sectors of the South African economy and the decline in international commodity prices have reduced their relative importance. However, the mining stocks and mining financials remain very important within the JSE.

The characteristics of the African markets sampled are shown below. The following definitions apply to the charts shown.

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[2] The selection of countries in the emerging Africa index followed the classification in the FTSE quality of market criteria (AFRICA), as at March 2014.

[3] The King Reports that regulate corporate governance practices in South Africa are very similar to the UK Cadbury Report and the US Sarbanes–Oxley Act (South African Institute of Directors, 2009).

[4] See the JSE website

Variable	Definition
GDP growth – Annual data	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2005 US dollars. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. *Data source: World Bank national accounts data and OECD National Accounts data files – World Bank Databank.*
GDP (in dollar terms) – Annual data	GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current US dollars. Dollar figures for GDP are converted from domestic currencies using single year official exchange rates. For a few countries where the official exchange rate does not reflect the rate effectively

	applied to actual foreign exchange transactions, an alternative conversion factor is used. *Data source: World Bank national accounts data and OECD National Accounts data files – World Bank Databank.*
Total value of stocks traded (% of GDP) – Annual data	Stocks traded refers to the total value of shares traded during the period. This indicator complements the market capitalisation ratio by showing whether market size is matched by trading. *Data source: World Bank national accounts data and OECD National Accounts data files – World Bank Databank.*
Turnover ratio of stocks traded – Annual data	Turnover ratio is the total value of shares traded during the period divided by the average market capitalisation for the period. Average market capitalisation is calculated as the average of the end-of-period values for the current period and the previous period. *Data source: World Federation of Exchanges database – World Bank Databank.*
Market capitalisation of listed companies (% of GDP) – Annual data	Market capitalisation (also known as market value) is the share price times the number of shares outstanding. Listed domestic companies are the domestically incorporated companies listed on the country's stock exchanges at the end of the year. Listed companies do not include

	investment companies, mutual funds, or other collective investment vehicles. *Data is as a percentage of GDP. Data source: World Federation of Exchanges database – World Bank Databank.*
Market capitalisation of listed companies (current US$) – Annual data	Market capitalisation (also known as market value) is the share price times the number of shares outstanding. Listed domestic companies are the domestically incorporated companies listed on the country's stock exchanges at the end of the year. Listed companies do not include investment companies, mutual funds, or other collective investment vehicles. *Data is in current US dollars. Data source: World Federation of Exchanges database – World Bank Databank.*

The share price of the JSE All Share Index is depicted in Figure 1.3 below, while its returns are shown in Figure 1.4.

Figure 1.3 Weekly time-series price of the Johannesburg Stock Exchange All Share Index

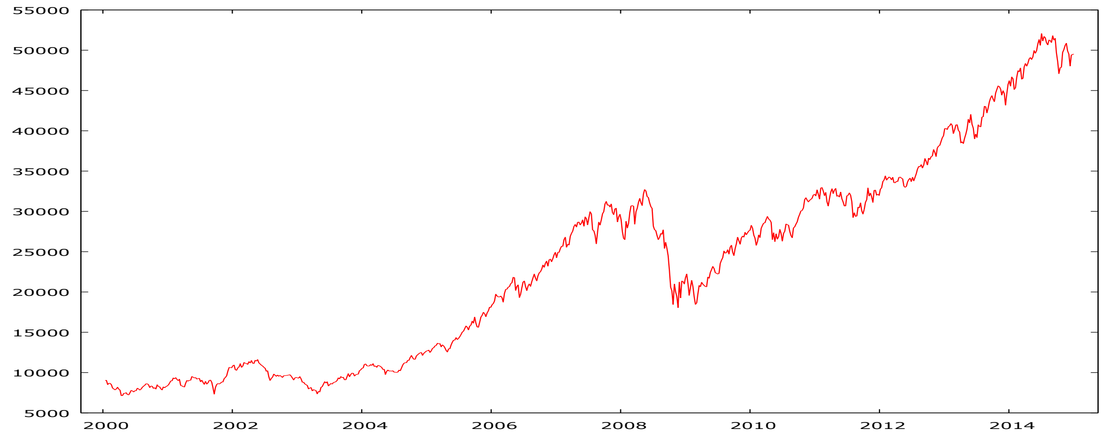


Figure 1.4 Weekly returns on the Johannesburg Stock Exchange All Share Index

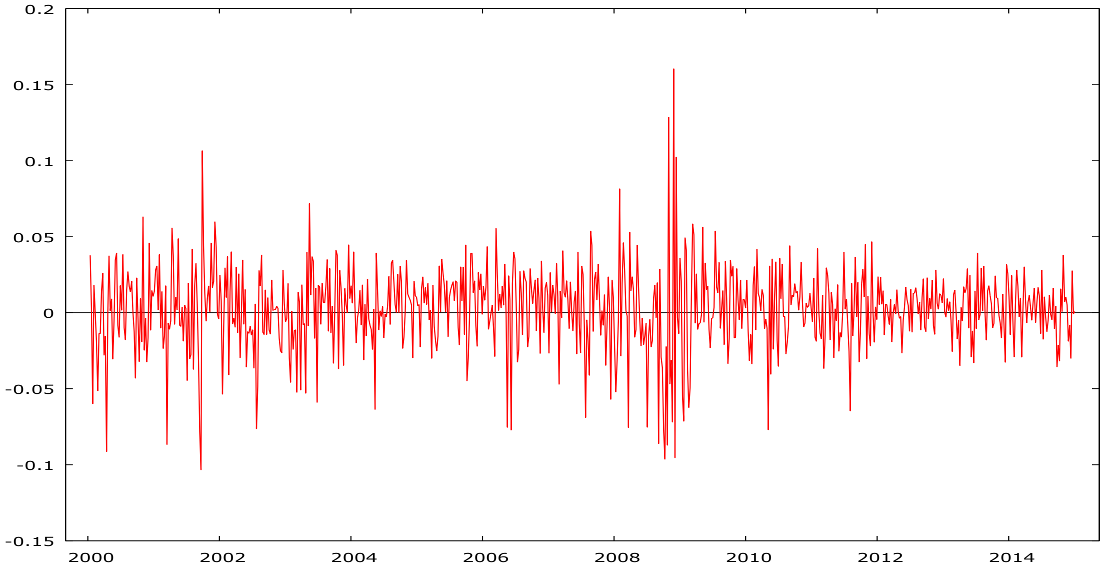


Table 1.1 Summary statistics of the returns on the Johannesburg Stock Exchange all share index

Mean	Median	Minimum	Maximum
0.0022	0.0036	−0.1033	0.1604
Std dev	CV	Skewness	Ex. kurtosis
0.0271	12.1789	−0.1620	3.3798

Figure 1.5 GDP growth for South African.

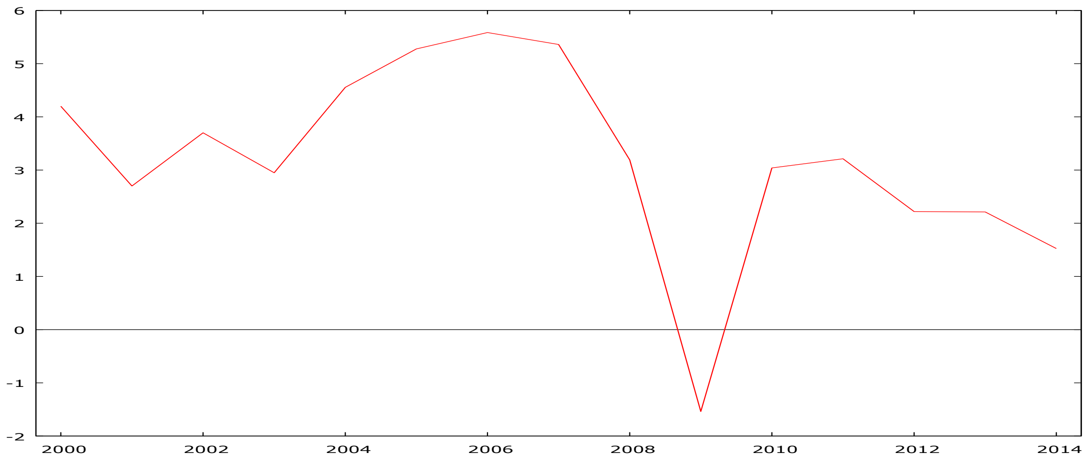


Figure 1.6 The total value to stocks traded (% of GDP) for the South African market

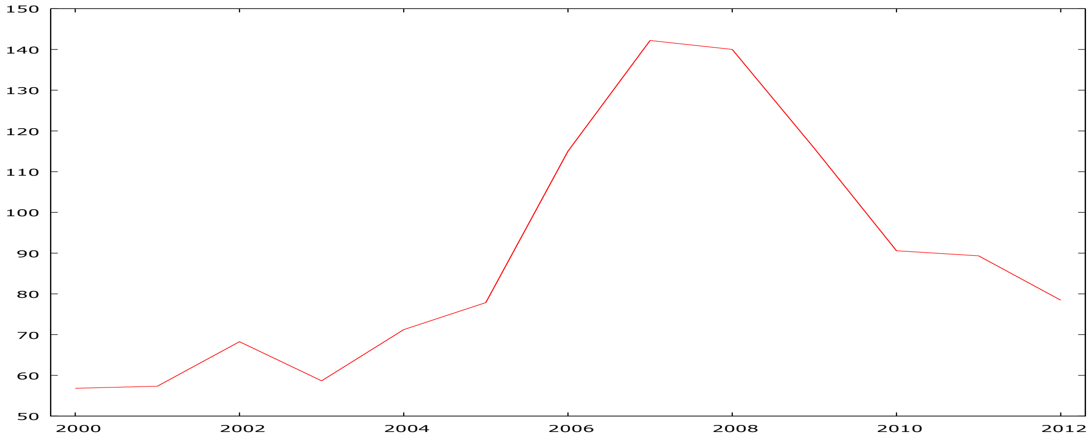


Figure 1.7 Turnover ratio of stocks traded (%) in the South African stock market

Figure 1.8 The market capitalisation of South Africa's listed companies (% of GDP)

Figure 1.9 Market capitalisation of South Africa's listed companies (current US$)

Table 1.2 Summary statistics of GDP growth, stocks traded to GDP (%), stock turnover ratio (%), market capitalisation to GDP (%) and market capitalisation in US$ for South Africa

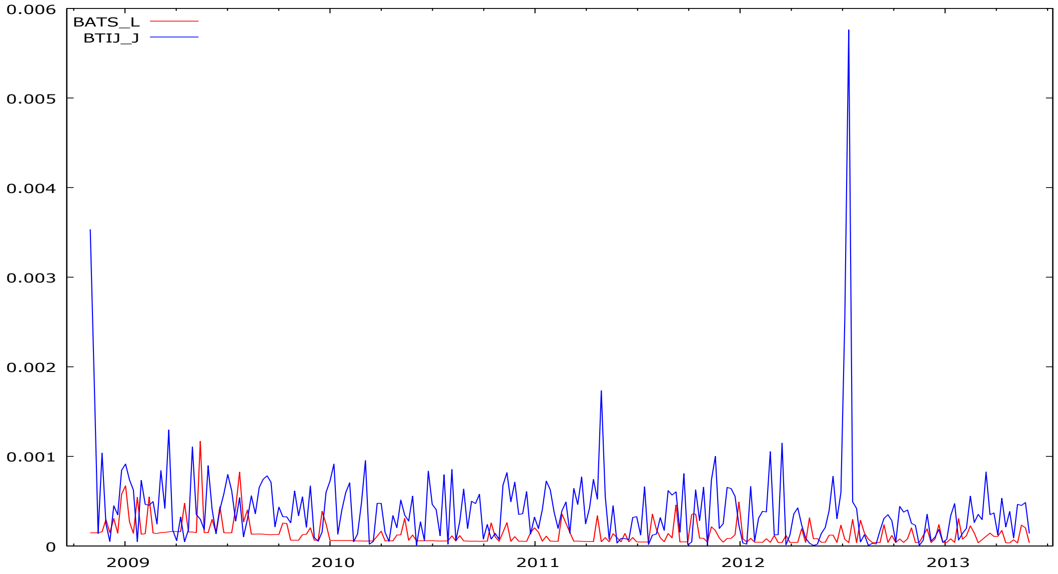
Variable	Mean	Median	Minimum	Maximum
GDP growth	3.21	3.19	-1.54	5.59
Stocks traded/GDP %	89.35	78.46	56.83	142.19
Stock turnover ratio %	49.51	48.80	33.16	64.26
Mkt cap/GDP	184.35	169.27	115.01	278.39
Mkt cap (US dollars)	487179000000	522975000000	139750000000	833548000000
Variable	Std dev.	CV	Skewness	Ex. kurtosis
GDP growth	1.80	0.56	−1.00	1.35
Stocks traded/GDP	29.95	0.34	0.64	−0.90
Stock turnover ratio	8.91	0.18	−0.12	−0.75
Mkt cap/GDP	51.44	0.28	0.55	−0.86
Mkt cap (US dollars)	224599000000	0.46	−0.26	−1.17

Figure 1.3 shows the time-series price of the JSE all share index between 2010 and 2015. The bull market on the trend is clear to see, except for the financial crisis of 2008. Figure 1.4 shows the log returns on the index with Table 1.1 showing a mean weekly return of 0.22%, a median of 0.36%, minimum value of −10.33% and a maximum value to 16.04%. The skewness and kurtosis values are −0.16 and 3.38, respectively. GDP growth in South Africa has been an average of 3.21% per annum, a maximum of 5.59% and a minimum of −1.54% during the 2008 financial crisis. On average, the total value of stocks traded as a percentage of GDP is 89.35% with a minimum of 56.83% and a maximum of 142.19%, with an average turnover of 49.51%, a minimum of 33.16% and a maximum of 64.26%.

The size of the South African market to GDP shown as the market capitalisation to GDP is an average of 184.35%, a minimum of 155.01% and a maximum of 278.39%. The market capitalisation in dollar terms is an average of 487,180,000,000 dollars, a minimum of 139,750,000,000 dollars and a maximum of 833,550,000,000 dollars.

A liquidity construct is examined below for the Johannesburg Stock Exchange compared with the London Stock Exchange.

Figure 1.10 Bid-ask spread for British American Tobacco listed on the London Stock Exchange (BATS_L) and Johannesburg Stock Exchange (BTIJ_L).



This presents a visible difference in the structure of the London and the Johannesburg markets, showing the bid-ask spread for British American Tobacco listed on the London Stock Exchange (BATS_L) and the bid-ask spread of British American Tobacco listed on the Johannesburg Stock Exchange (BTIJ_L). These are calculated using$\left(\frac{(Ask_W - Bid_W)}{(Ask_W + Bid_W)/2}\right)$, as identified in Hearn and Piesse (2009). It is quite clear that BTIJ_L has higher spreads than BATS_L through the period.

This demonstrates the possible existence of different systematic factors that affect securities in these markets, which will also affect pricing. The difference in the bid-ask spread particularly highlights the presence of severe illiquidity within the African market, hence the modelling approach will also account for the effect of liquidity.

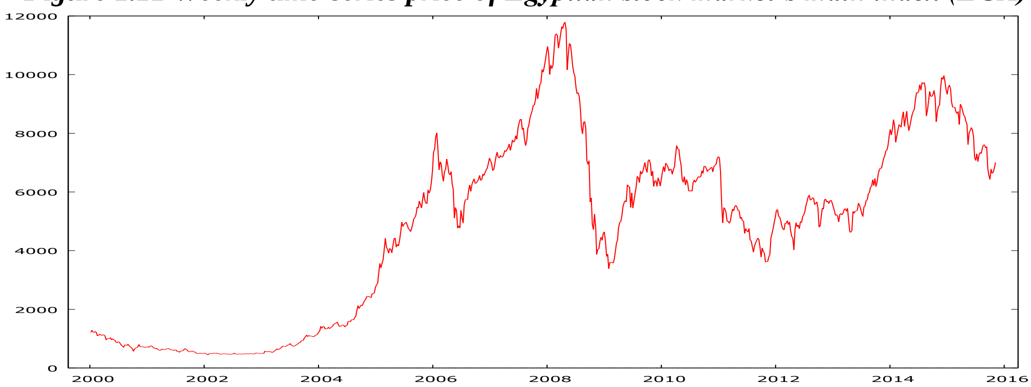
1.6.1.2 Egypt

The Egyptian stock market was formed through the integration of the Alexandria Stock Exchange, which was established in 1988, and the Cairo Stock Exchange, established in 1903. Trading takes place electronically via a listed securities market, a primary dealers bond market and an OTC market. Settlement is assisted by a central depository that is largely compliant with G30[5] recommendations along with large and well-capitalised custodian banks,[6] which supports overseas investors. In 2003, a code of corporate governance was established to enshrine the best principles of OECD guidelines by a committee formed from CASE and the 10 largest companies.

In the 1980s, the Egyptian government opened up the market to local and foreign investors by embarking on a privatisation attempt, which was encouraged by the International Monetary Fund (IMF). According to Omran (2005), this led to the rapid growth of participation in the stock market by both individuals and institutions. As highlighted in Smith, Jefferis and Ryoo (2002), the Egyptian stock market witnessed an average growth rate of turnover of about 60% between 1988 and 1997. For an excellent analysis of the rapid growth of the Egyptian economy, see Shinnawy and Handoussa (2003).

Figures 1.11 and 1.12 show the time-series plot of the Egyptian stock market's main index (EGX) and the log returns respectively.

Figure 1.11 Weekly time-series price of Egyptian stock market's main index (EGX)



[5]G30 relates to the Group of Thirty, which is the most influential body to encourage the standardisation and improvement in global securities administration.

[6]As stated on the Cairo Alexandria Stock Exchange website.

Figure 1.12 Weekly returns for the Egyptian stock market's main index (EGX)

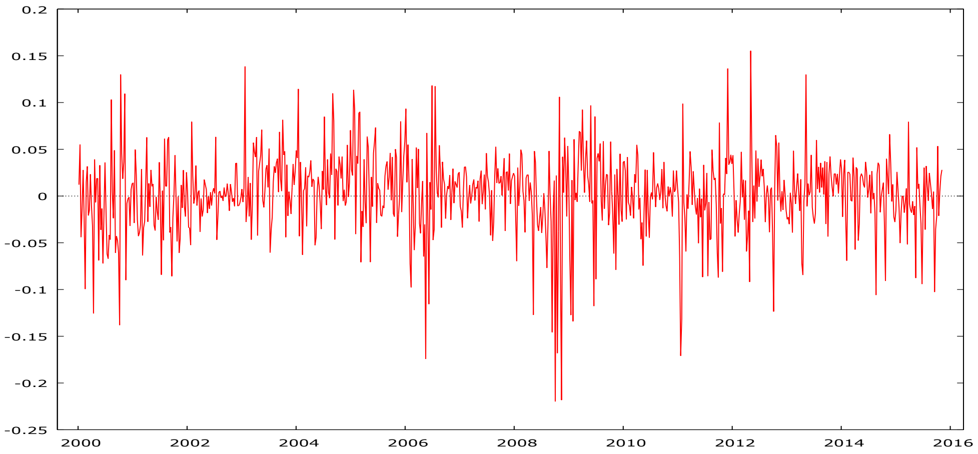


Table 1.3 Summary statistics for the returns on the Egyptian Stock Exchange EGX Share Index

Mean	Median	Minimum	Maximum
0.0021	0.0045	−0.2196	0.1552
Std dev.	CV	Skewness	Ex. kurtosis
0.0426	19.976	−0.6768	3.3169

Figure 1.13 GDP growth for Egypt

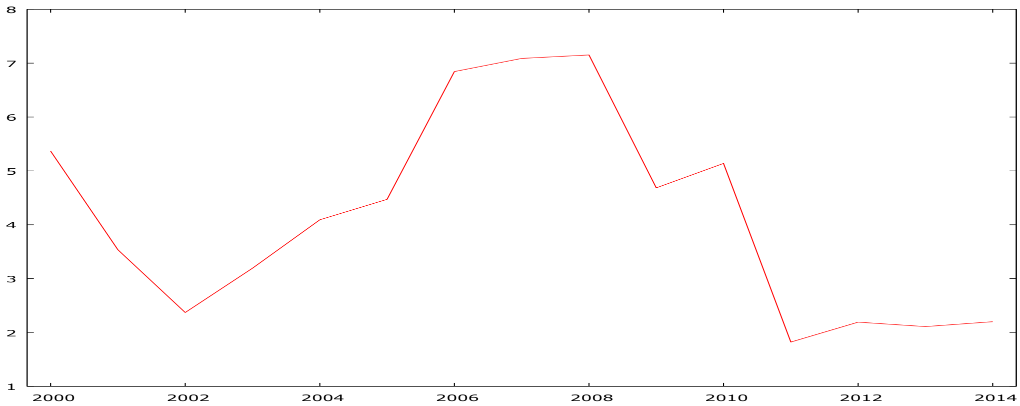


Figure 1.14 GDP (in dollar terms) for the Egyptian market

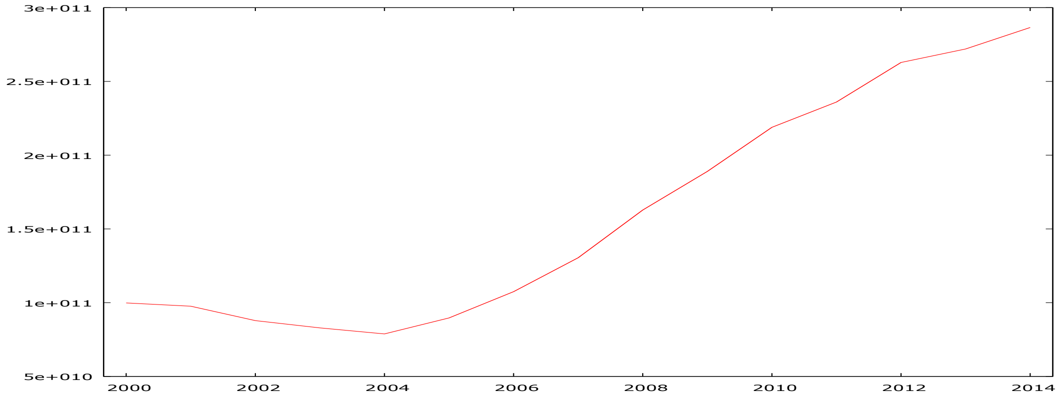


Figure 1.15 Total value to stocks traded (% of GDP) for the Egyptian market

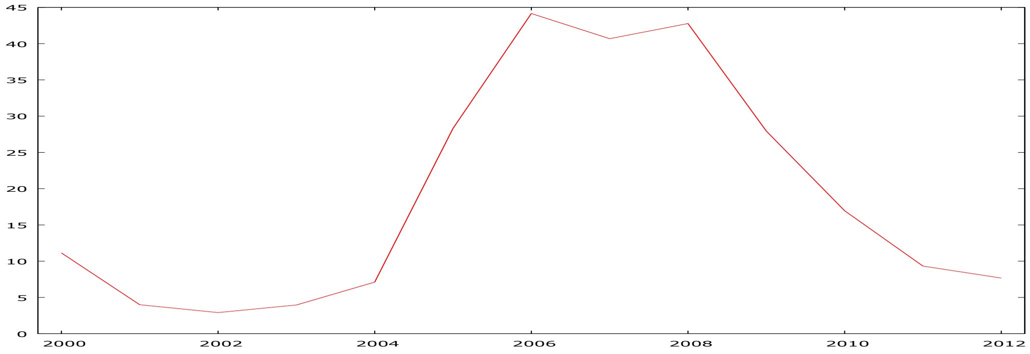


Figure 1.16 Turnover ratio of stocks traded (%) in the Egyptian market

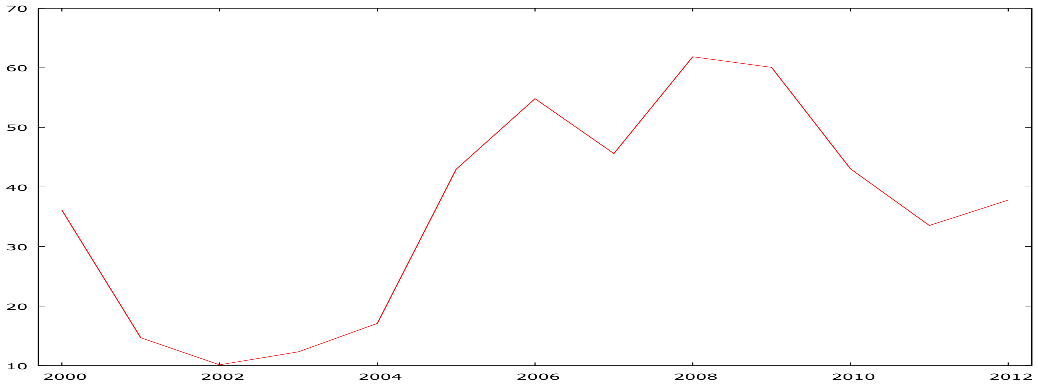


Figure 1.17 Market capitalisation of Egypt's listed companies (% of GDP)

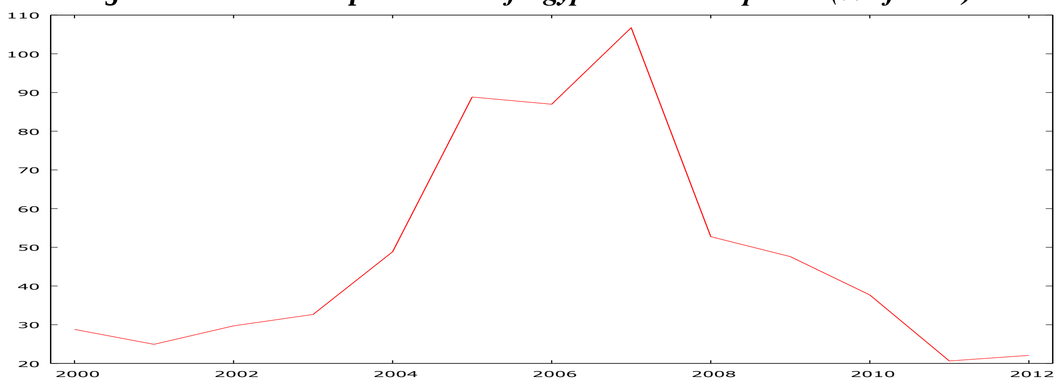


Figure 1.18 Market capitalisation of Egypt's listed companies (current US$)

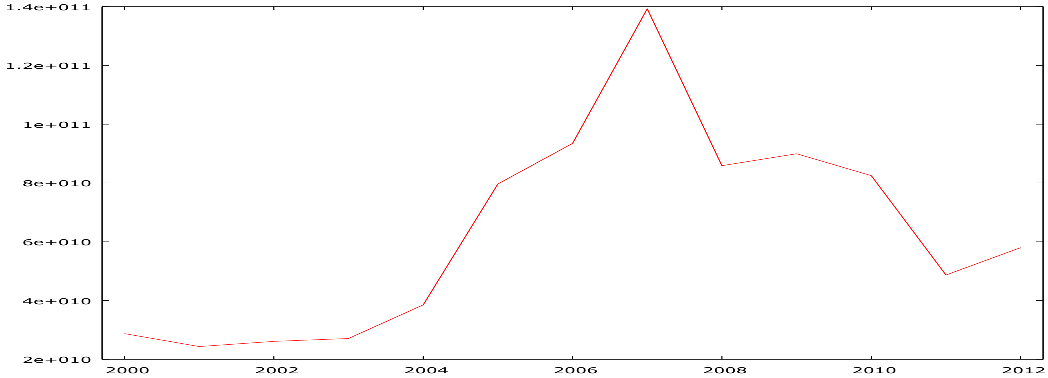


Table 1.4 Summary statistics of GDP growth, GDP (USD), stocks traded to GDP (%), stock turnover ratio (%), market capitalisation to GDP (%) and market capitalisation in USD for Egypt

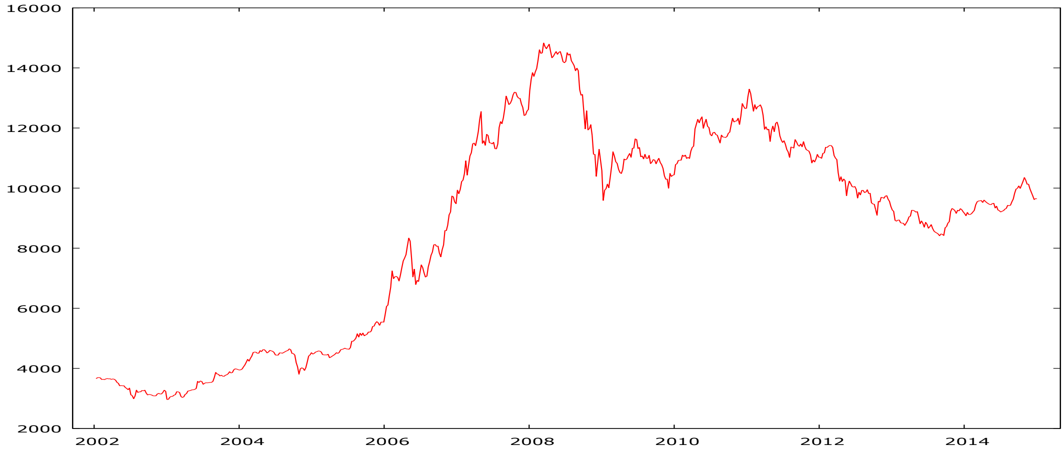
Variable	Mean	Median	Minimum	Maximum
GDP growth (%)	4.15	4.09	1.82	7.15
GDP (US$)	160184000000	130479000000	78845200000	286538000000
Stocks traded/GDP (%)	18.99	11.14	2.91	44.16
Stock turnover (%)	36.16	37.79	10.14	61.85
Mkt cap/GDP (%)	48.32	37.69	20.63	106.75
Mkt cap (US dollars)	63247700000	58008000000	24335100000	139289000000
Variable	Std dev.	CV	Skewness	Ex. kurtosis
GDP growth (%)	1.88	0.45	0.36	−1.17
GDP (US dollars)	77010800000	0.48	0.45	−1.40
Stocks traded/GDP	15.74	0.83	0.57	−1.28
Stock turnover (%)	17.89	0.50	−0.14	−1.22
Mkt cap/GDP (%)	28.37	0.59	0.96	−0.45
Mkt cap (US dollars)	35127300000	0.56	0.59	−0.45

The average GDP growth for Egypt was 4.15% per annum, with a minimum of 1.82% and a maximum of 7.15%. Average stocks traded to GDP was 18.99%, which is lower than 89.35% in South Africa. A minimum value of 2.91% and a maximum of 44.16% were reported within the period. Stock turnover for the Egyptian stock market was an average of 36.16%, with a minimum and maximum of 10.14% and 61.85%, respectively. The market capitalisation to GDP was an average of 48.32%, which is significantly lower than reported in the South African market. The minimum and maximum market capitalisation to GDP were 20.63% and 106.75%, respectively. Egypt's market capitalisation was an average of $63,247,700,000, with a minimum of $24,335,100,000 and a maximum of $139,289,000,000.

1.6.1.3 Morocco

Established in 1929, the Bourse de Casablanca trades electronically with terminals located in the local brokerage community. Settlement by MAROCLEAR, the national CSD established in 1998[7] is also G30-compliant. By reporting trading electronically to both local and international vendors such as Reuters and Bloomberg, the Bourse de Casablanca is able to attract overseas investors. In line with changes in political, economic and administrated governance institutions, corporate governance legislation in Morocco has undergone considerable modernisation. However, according to Hearn and Piesse (2009), a formal code of corporate governance was only recently enacted in February 2007, through the establishment of a National Commission of Corporate Government in Casablanca (National Commission on Corporate Governance 2008). This largely follows the OECD's best practice guideline.

Figure 1.19 Weekly time-series price of the Casablanca SE All Share Index



[7]See Bourse de Casablanca website, 2009.

Figure 1.20 Weekly returns of the Casablanca SE All Share Index

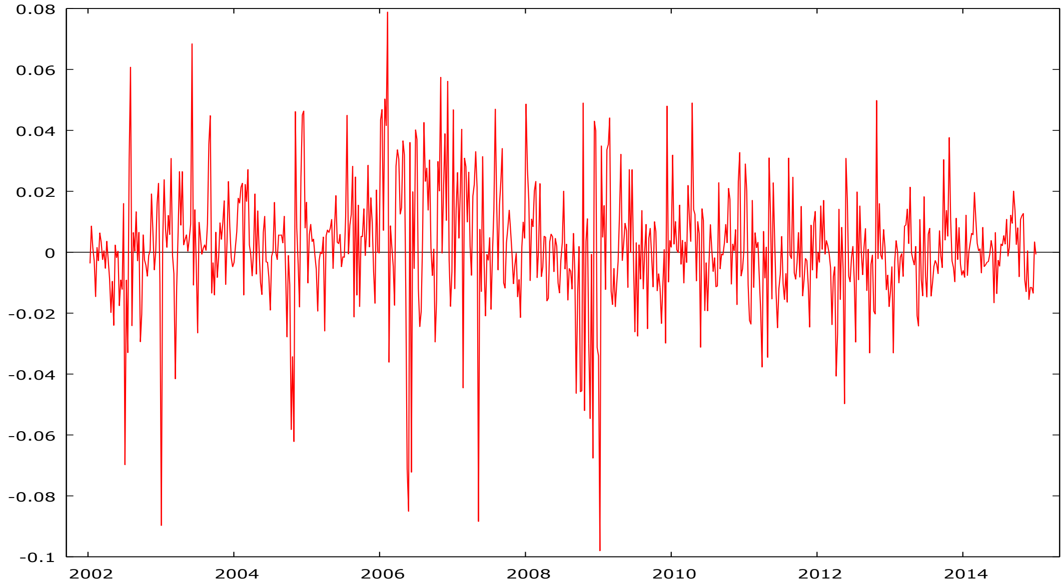


Table 1.5 Summary statistics of the returns on the Casablanca SE All Share Index

Mean	Median	Minimum	Maximum
0.0014	0.0009	−0.0980	0.0789
Std dev.	CV	Skewness	Ex. kurtosis
0.0201	14.077	−0.4927	3.6377

Figure 1.21 GDP growth for Morocco

Figure 1.22 GDP (in dollar terms) for Morocco

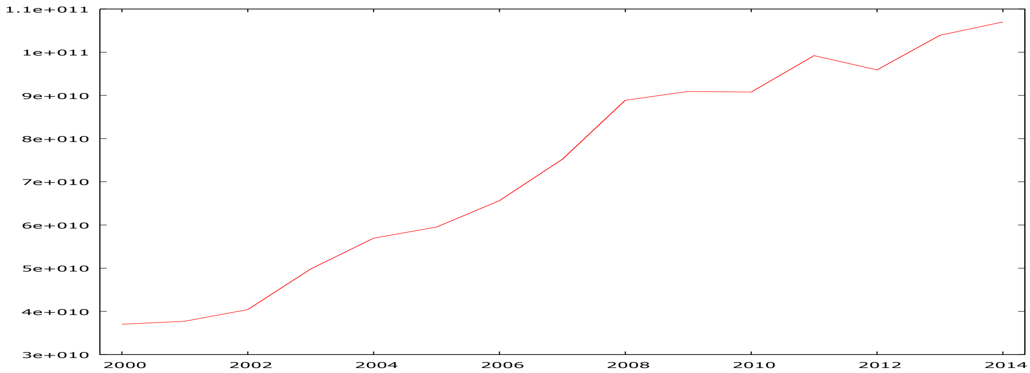


Figure 1.23 The total value of stocks traded (% of GDP) for the Moroccan market

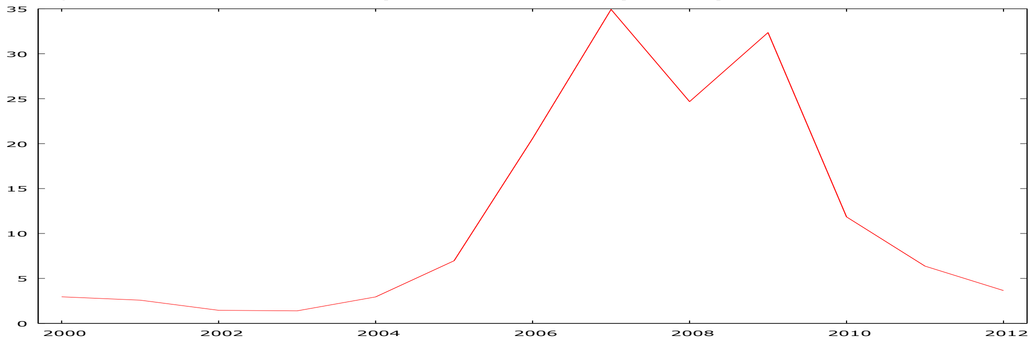


Figure 1.24Turnover ratio of stocks traded on the Moroccan market

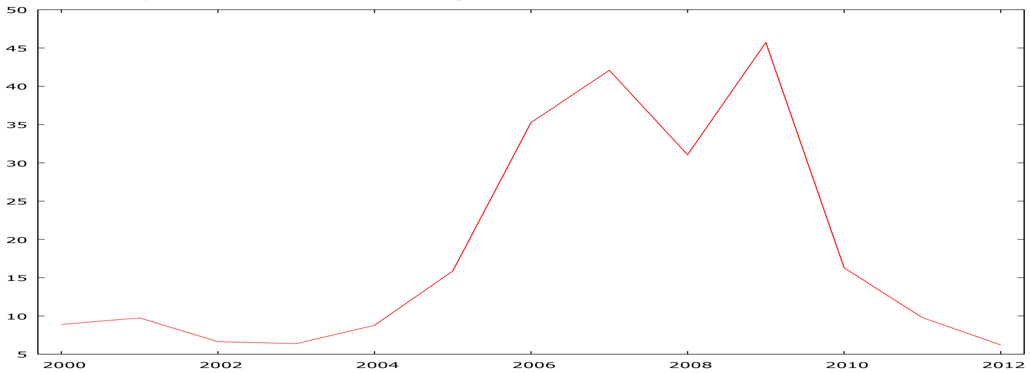


Figure 1.25 Market capitalisation of Morocco's listed companies (% of GDP)

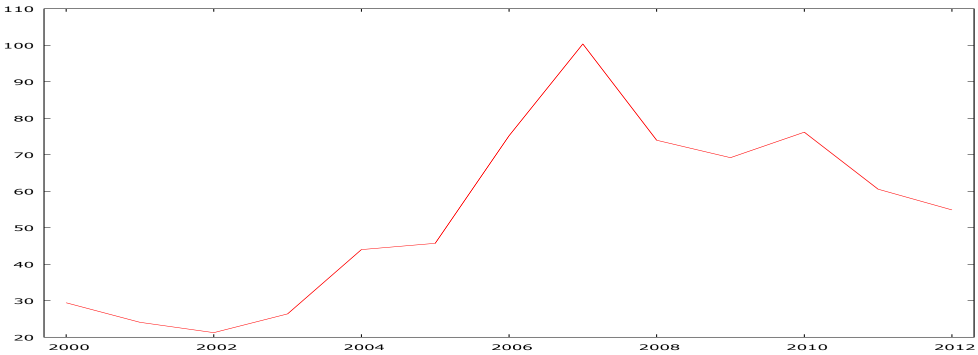


Figure 1.26 Market capitalisation of listed companies (current US$)

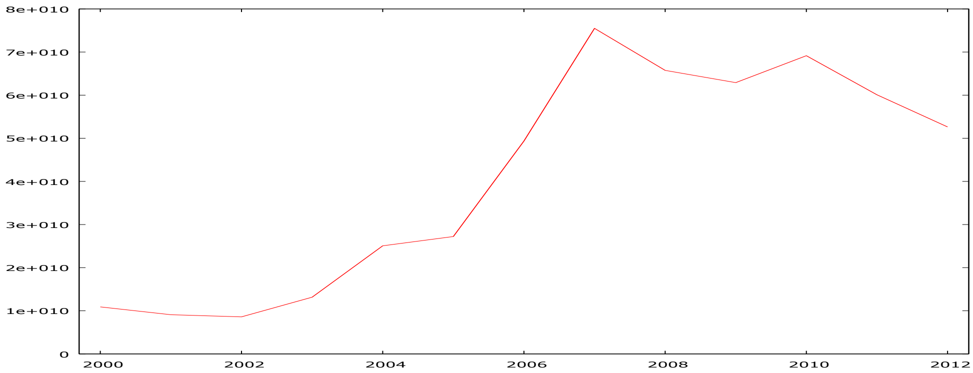


Table 1.6 Summary statistics of GDP growth, stocks traded to GDP (%), stock turnover ratio (%), market capitalisation to GDP (%) and market capitalisation in US$ for Morocco

Variable	Mean	Median	Minimum	Maximum
GDP growth (%)	4.37	4.38	1.59	7.76
GDP (US$)	73260700000	75223600000	37020600000	107005000000
Stocks traded/GDP	11.75	6.37	1.39	34.93
Stock turnover (%)	18.67	9.78	6.21	45.73
Mkt cap/GDP	53.95	54.88	21.26	100.36
Mkt Cap (US$)	40723100000	49360000000	8590570000	75494600000
Variable	Std dev.	CV	Skewness	Ex. kurtosis
GDP growth (%)	1.85	0.42	0.46	−0.76
GDP (US$)	25138800000	0.34	−0.17	−1.46
Stocks traded/GDP	12.17	1.04	0.91	−0.73
Stock turnover (%)	14.51	0.78	0.86	−0.89
Mkt cap/GDP	24.60	0.46	0.20	−0.98
Mkt cap (US$)	25556700000	0.63	−0.09	−1.64

Average GDP growth is 4.37%, which is higher than the 4.15% in Egypt, with minimum and maximum values of 1.59% and 7.76%, respectively. Average GDP (US$) was $73,260,700,000, with a minimum of $37,020,600,000 and a maximum of $107,005,000,000. Average stocks traded were 11.75% of GDP with a minimum and maximum value of 1.39% and 34.93%, respectively. Stock turnover for the Moroccan stock market was an average of 18.67%, with a minimum of 6.21% and a maximum of 45.73%. The market capitalisation to GDP was an average of 59.95%, which is higher than reported in Egypt but lower than reported in South Africa. The minimum and maximum market capitalisation to GDP were 21.25% and 100.36%, respectively. Morocco’s market capitalisation was an average of $40,723,100,000, with a minimum of $8,590,570,000 and a maximum of $75,494,600,000.

1.6.2 The frontier African market index

The constituents of the frontier African market index are Botswana, Cote d'Ivoire, Ghana, Kenya, Mauritius, Nigeria and Tunisia.[8] However, due to the paucity of data, Ghana and Mauritius will be excluded.

1.6.2.1 Botswana

The Botswana Stock Exchange (BSE) was established in 1989[9] and given the responsibility to operate and regulate the equities and fixed-interest securities markets. At establishment, the exchange was referred to as the Botswana Share Market (BSM) but this was changed to BSE in 1995. BSE was to be pivotal to Botswana's financial system, as an avenue for the government, quasi-government and the private sector to raise debt and equity capital in the capital market. According to the BSE website, the BSE has averaged a 24% aggregate return in the past decade, making it one of the best-performing stock exchanges in Africa.

The BSE has also grown in terms of market capitalisation, becoming the third largest stock exchange by market capitalisation in southern Africa. As at January 2016, the BSE had 20 domestic companies listed on its main board, with another two companies listed on its venture capital board. For foreign companies, it has four companies on its main board and a further six venture capital companies. It also has four exchange-traded funds. Brokers consist of Imara Capital Securities, Motswedi Securities, Stockbrokers Botswana and African Alliance Botswana Securities. The exchange also has other partners such as primary dealers, custodians and transfer secretaries.

The figure below shows the weekly time-series trade price of the Botswana Stock Exchange DC index.

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[8] The selection of countries in the emerging Africa index followed the classification in the FTSE quality of market criteria (AFRICA), as at March 2014.
[9] Source: Botswana Stock Exchange website - http://www.bse.co.bw/abt_us/role_in_botswana.php

Figure 1.27 Weekly time-series price of the Botswana Stock Exchange DC index

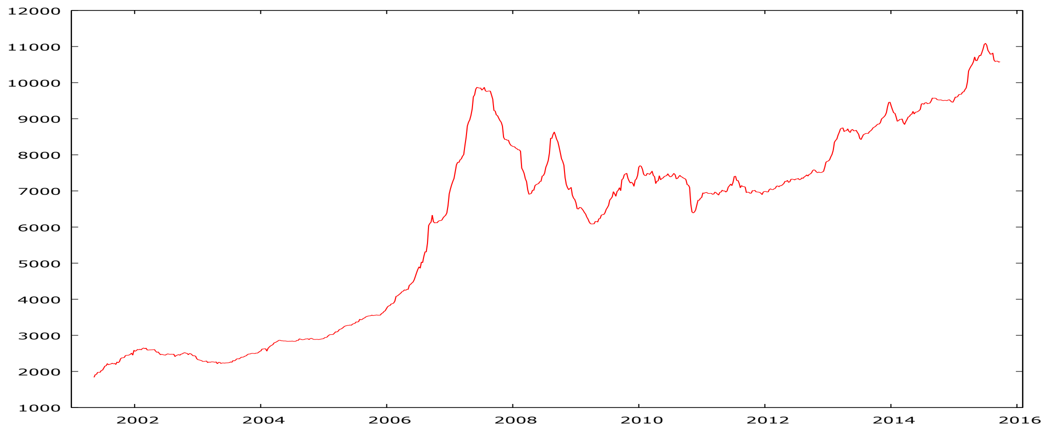


Figure 1.28 Weekly log returns of the Botswana Stock Exchange DC index

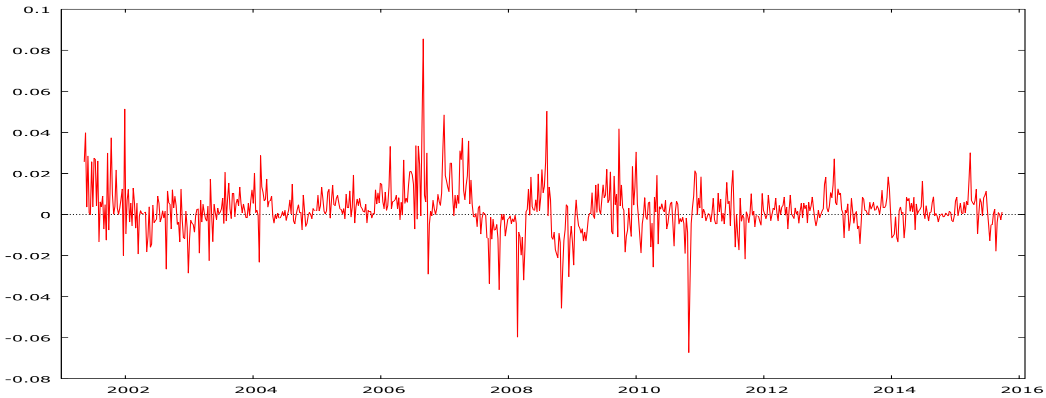


Table 1.7 Summary statistics of the returns on the Botswana Stock Exchange DC index

Mean	Median	Minimum	Maximum
0.0024	0.0018	−0.0673	0.0855
Std dev.	CV	Skewness	Ex. kurtosis
0.0118	4.9696	0.3357	7.6683

Figure 1.29 GDP growth for Botswana

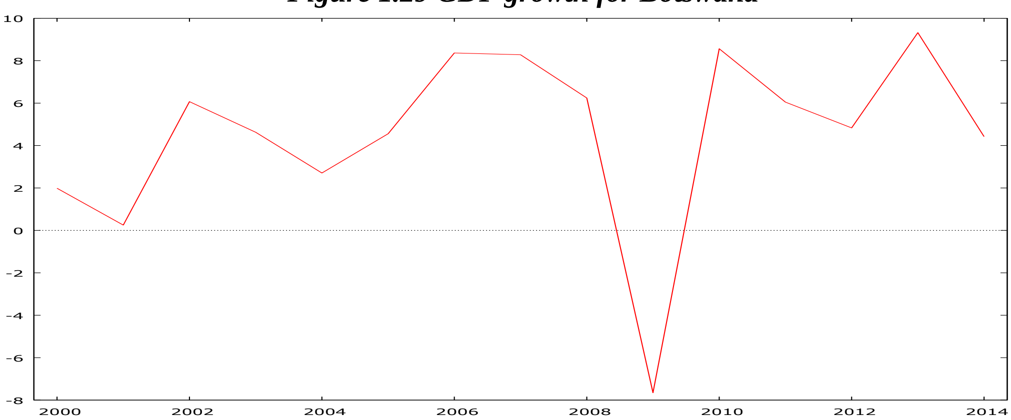


Figure 1.30 GDP in US$ for Botswana

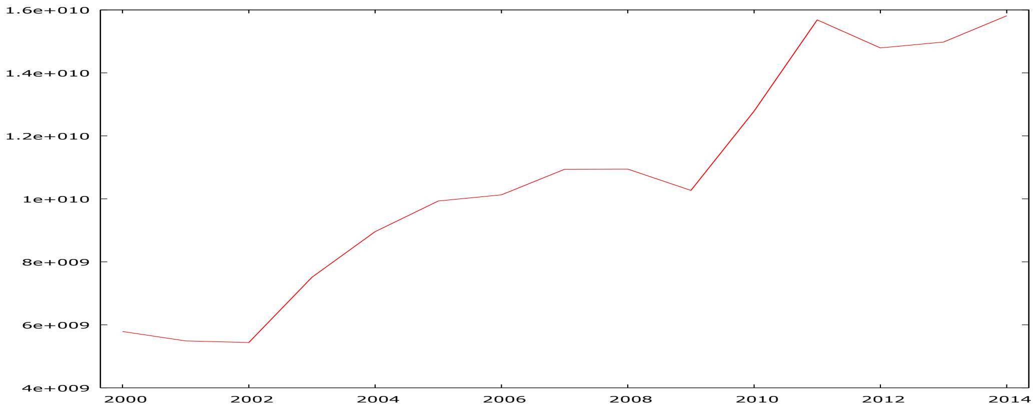
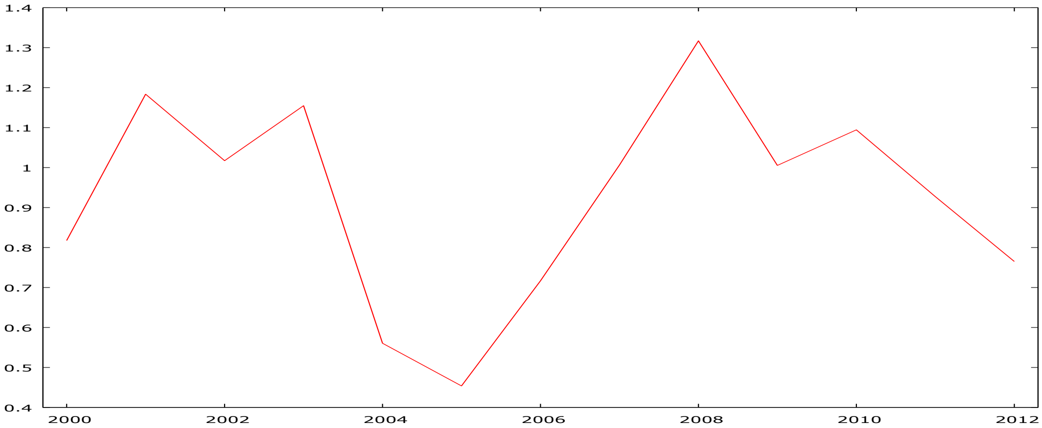


Figure 1.31 Total value to stocks traded (% of GDP) for the Botswana stock market



No data was found for turnover ratio of stocks traded, market capitalisation (% of GDP) and market capitalisation (US$) for Botswana.

Table 1.8 Summary statistics of GDP growth, GDP (US$) and stocks traded to GDP (%) for Botswana

Variable	Mean	Median	Minimum	Maximum
GDP growth (%)	4.57	4.83	−7.65	9.32
GDP (US$)	10630000000	10267000000	5438900000	15813000000
Stocks traded/GDP	0.93	1.01	0.45	1.32
Variable	Std dev.	CV	Skewness	Ex. kurtosis
GDP growth (%)	4.24	0.93	−1.59	2.64
GDP (US$)	3622300000	0.34	0.013	−1.16
Stocks traded/GDP	0.25	0.27	−0.38	−0.71

Botswana's mean GDP growth for the period was 4.57%, which is higher than in South Africa (3.21%), Egypt (4.15%) and Morocco (4.37%) in the emerging African market. Stock traded to GDP is very low at 0.93% compared to 89.35% in South Africa and 18.99% in Egypt and 11.75% in Morocco.

1.7.2.2 Cote d'Ivoire (BRVM)

According to Hearn (2012), the Bourse Regionale des Valeurs Mobilieres SA (BRVM), which stands for Regional Securities Exchange SA, is a regional stock exchange serving members of the Union Monétaire et Économique de l'Afrique de l'Ouest (UMEAO) which includes Benin, Burkina Faso, Guinea-Bissau, Cote d'Ivoire, Mali, Niger, Senegal and Togo. BRVM started operations in 1998 and operates entirely electronically. The mission of the exchange is to organise the securities market, disseminate market information and promote the market.

According to *African Markets*,[10] BRVM ranks as the topmost performing stock market in Africa, in terms of its index of all listed securities in 2015, with a 17.77% increase in its composite index (BRVM composite). This is largely due to the continued economic growth in Cote d'Ivoire and throughout the West African Economic and Monetary Union (WAEMU), and the prospect of regional development that makes it attractive to investors.

The figure below shows the weekly time-series trade price of the Abidjan SE Industrials index.

[10] https://www.african-markets.com/en/stock-markets/brvm/brvm-african-stock-market-champion-for-2015

Figure 1.32 Weekly time-series price of the Abidjan SE Composite index

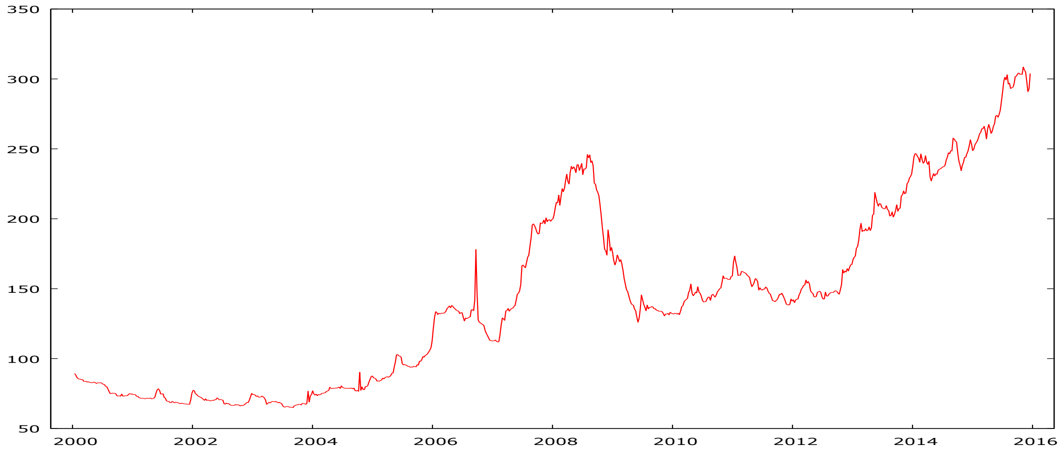


Figure 1.33 Weekly returns of the Abidjan SE Composite index

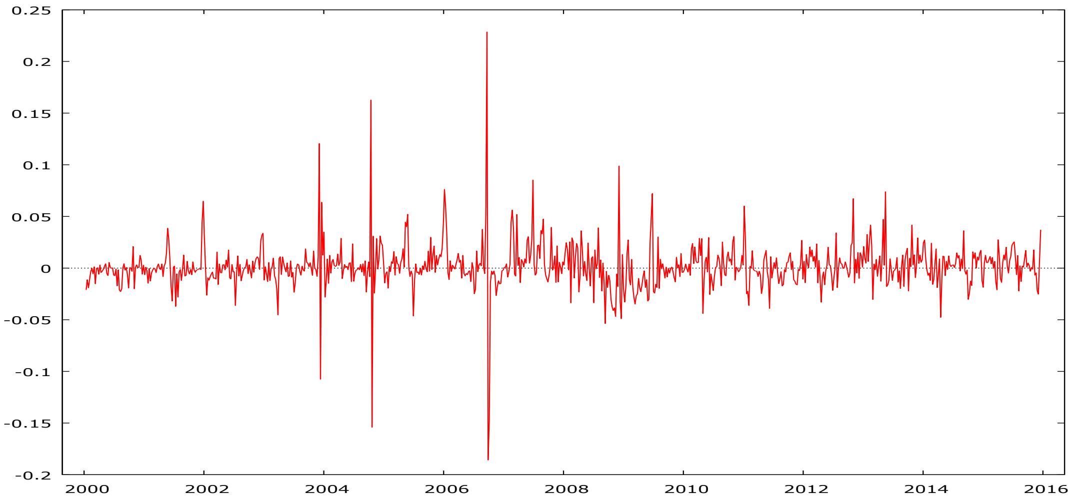


Table 1.9 Summary statistics of the returns on the Abidjan SE Industrials index

Mean	Median	Minimum	Maximum
0.0015	0.0003	−0.1858	0.2286
Std dev.	CV	Skewness	Ex. kurtosis
0.0228	15.774	0.6858	25.707

Figure 1.34 GDP growth for Cote d'Ivoire

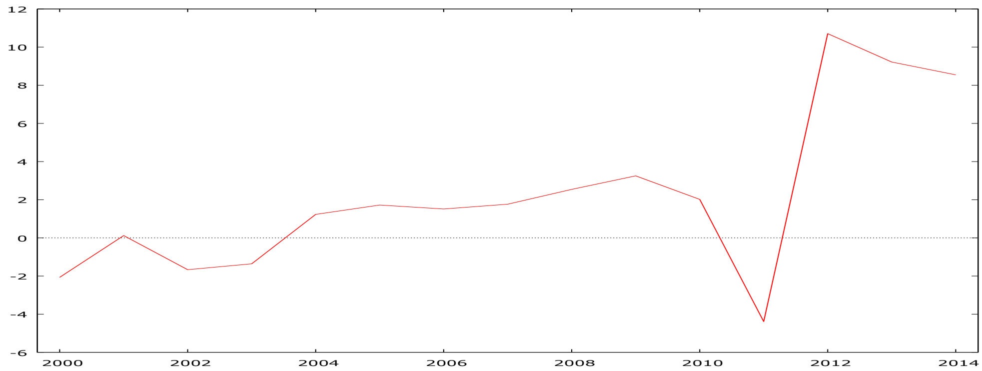


Figure 1.35 GDP (US$) for Cote d'Ivoire

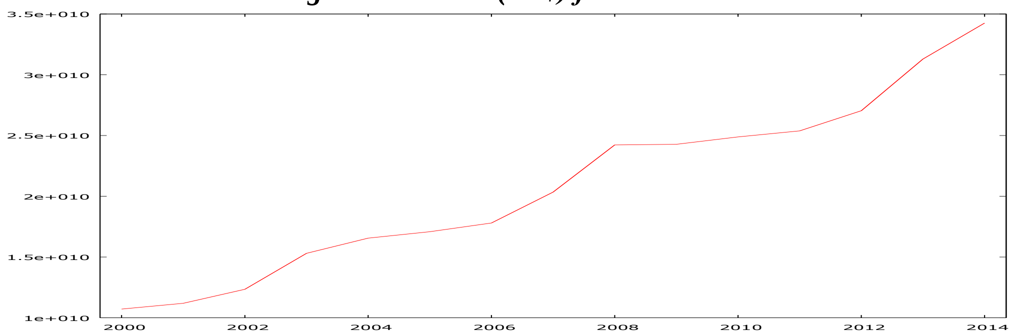


Figure 1.36 Market capitalisation of Cote d'Ivoire's listed companies (% of GDP), incl. 2000-2002

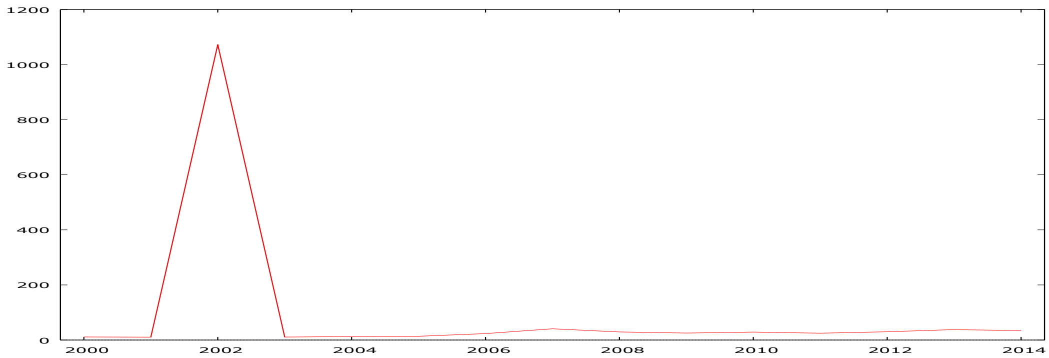


Figure 1.37 Market capitalisation of Cote d'Ivoire's listed companies (% of GDP), excl. 2000-2002

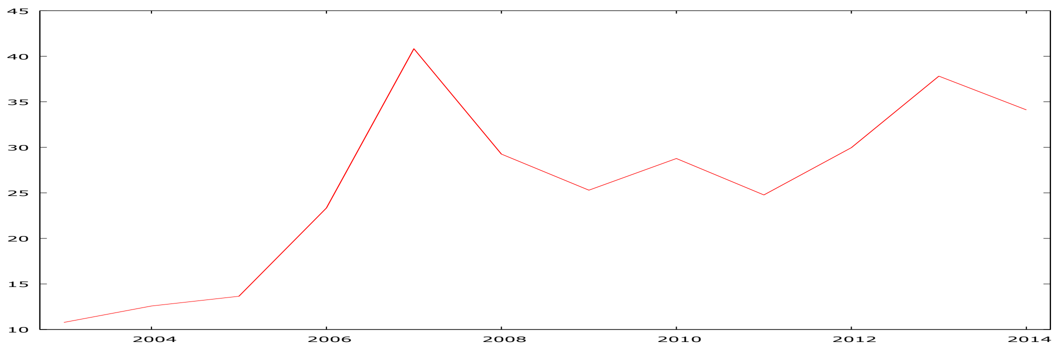


Figure 1.38 Market capitalisation of listed companies (current US$), incl. 2000-2002

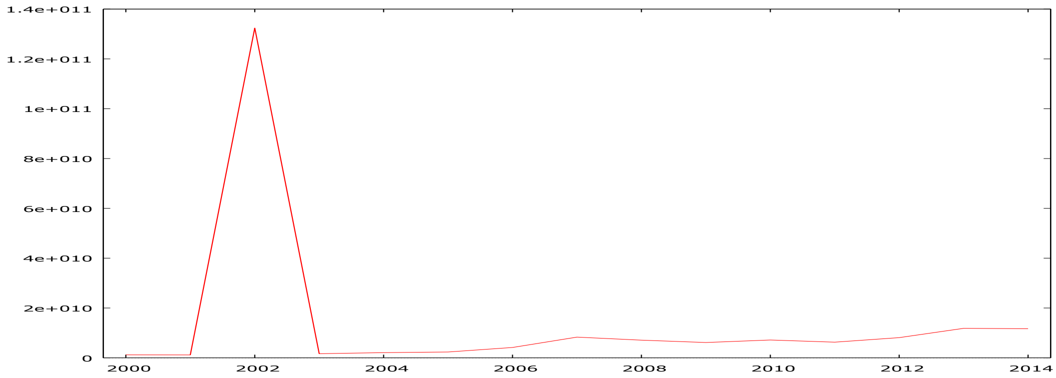
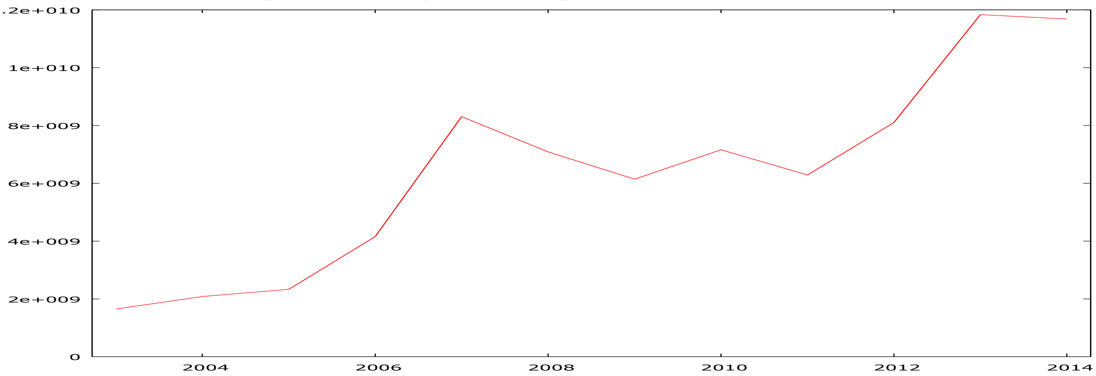


Figure 1.39 Market capitalisation of listed companies (current US$), excl. 2000-2002



No data was found for turnover ratio of stocks traded, total value of stocks traded (% of GDP) and turnover of stocks traded for Cote d'Ivoire. The GDP data for 2002 seems to have been stored in the world bank database in error, hence figures 1.36 and 1.38 exclude years 2000 to 2002.

Table 1.10 Summary statistics of GDP growth, GDP (US$), market capitalisation to GDP (%) and market capitalisation in US$ for Cote d'Ivoire

Variable	Mean	Median	Minimum	Maximum
GDP growth (%)	3.06	1.89	−4.39	10.71
GDP (US$)	23204000000	24251000000	15307000000	34254000000
Mkt cap/GDP (%)	25.93	27.04	10.78	40.82
Mkt cap (US$)	6401900000	6687700000	1650100000	11834000000
Variable	Std dev.	CV	Skewness	Ex. kurtosis
GDP growth (%)	4.39	1.43	0.37	−0.54
GDP (US$)	5980300000	0.26	0.34	−0.86
Mkt cap/GDP (%)	9.69	0.37	−0.22	−0.96
Mkt cap (US$)	3409800000	0.532	0.13	−0.93

The GDP growth for Cote d'Ivoire was a mean of 3.06%, which is lower than all of South Africa, Egypt, Morocco and Botswana. Market capitalisation to GDP ratio was also low (25.93%) compared with South Africa (184.35%), Egypt (48.32%) and Morocco (53.95%)

Data on GDP growth and GDP at market prices (current US$) for the other BRVM countries of Benin, Burkina Faso, Guinea-Bissau, Mali, Niger, Senegal and Togo are analysed but not included in this study.

1.7.2.3 Kenya

The Nairobi Stock Exchange (NSE) was registered under the Societies Act (1954) as a voluntary association of stockbrokers.[11] Although dealing in shares actually commenced in the 1920s, it was only based on a gentlemen's agreement, with no physical trading floor. Up until 1970, the NSE comprised public companies from Kenya, Tanzania and Uganda, operating as a regional market in East Africa, but with political regime change in the region, companies domiciled in Tanzania and Uganda delisted. In 1991, NSE was registered as a private company limited by shares. Share trading became based on an open outcry system in Nairobi. In 1994, the exchange set up a computerised delivery and settlement system (DASS).

The Central Depository and Settlement Corporation Limited (CDSC) was incorporated under the Companies Act in 1999 and in 2001 the market at the NSE was split into the Main Investment Market Segment (MIMS), Alternative Investment Market Segment (AIMS) and the Fixed Income Securities Market Segment (FISMS). In 2004, the process of clearing and settlement of shares traded in Kenya's capital market became automated through the central depository system. The NSE All Share Index (NASI) was introduced in 2008, while in 2011 the equity settlement cycle moved from the previous T+4 settlement cycle to the T+3 settlement cycle.

The figure below shows the weekly time-series trade price of the NSE All Share Index

[11]Nairobi Securities Exchange - https://www.nse.co.ke/nse/history-of-nse.html

Figure 1.40 Weekly time-series price of the Nairobi Stock Exchange All Share Index

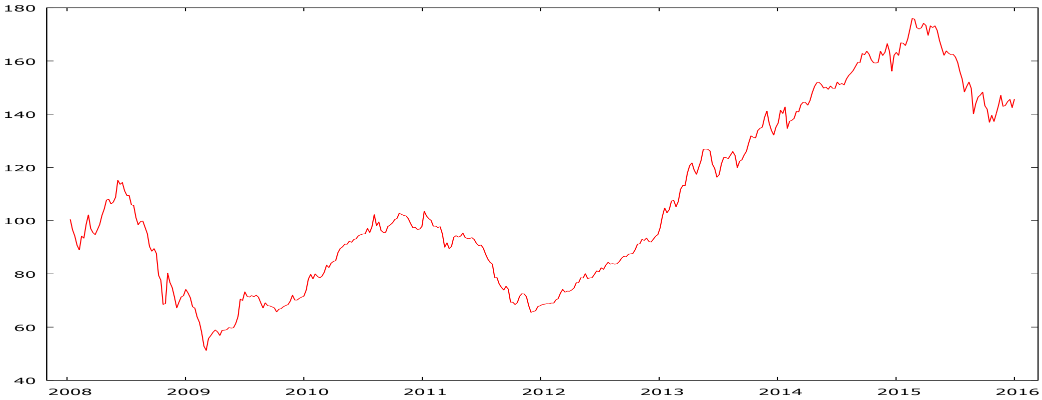


Figure 1.41 Weekly returns of the Nairobi Stock Exchange All Share Index

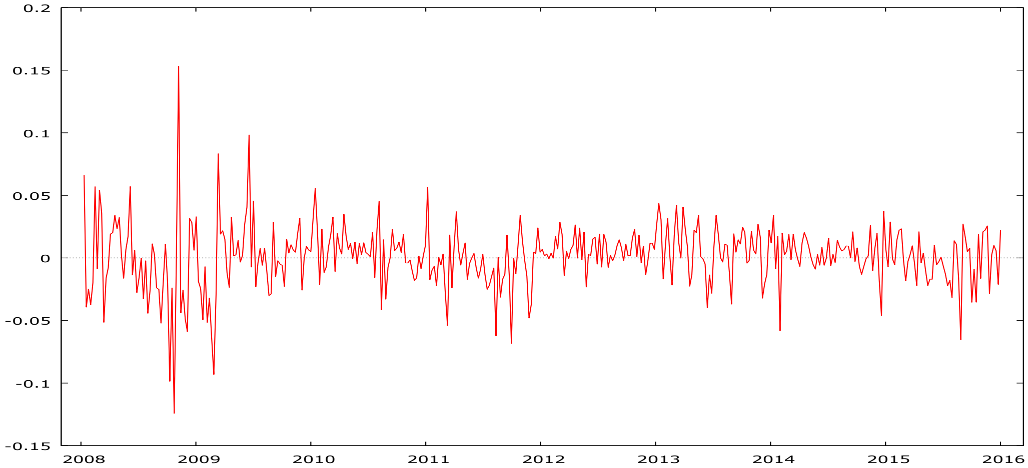


Table 1.11 Summary statistics of the returns on the Nairobi Stock Exchange All Share Index

Mean	Median	Minimum	Maximum
0.0011	0.0024	−0.1241	0.1531
Std dev.	CV	Skewness	Ex. kurtosis
0.0251	23.857	−0.0373	5.6780

Figure 1.42 GDP growth for Kenya

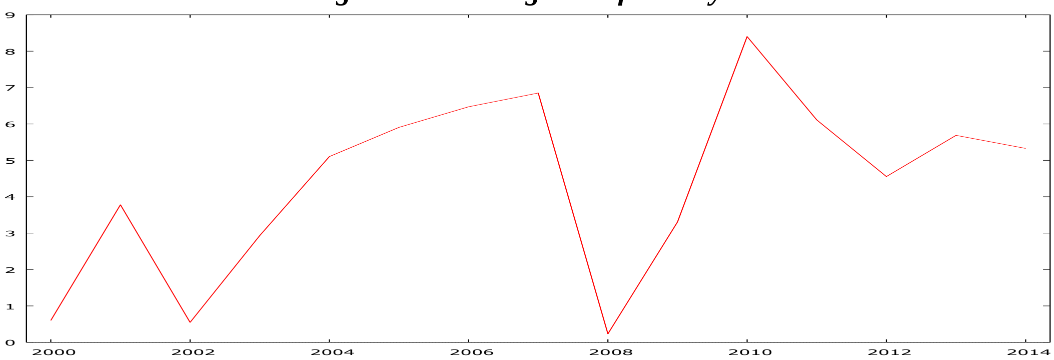


Figure 1.43 Kenya's GDP in US$

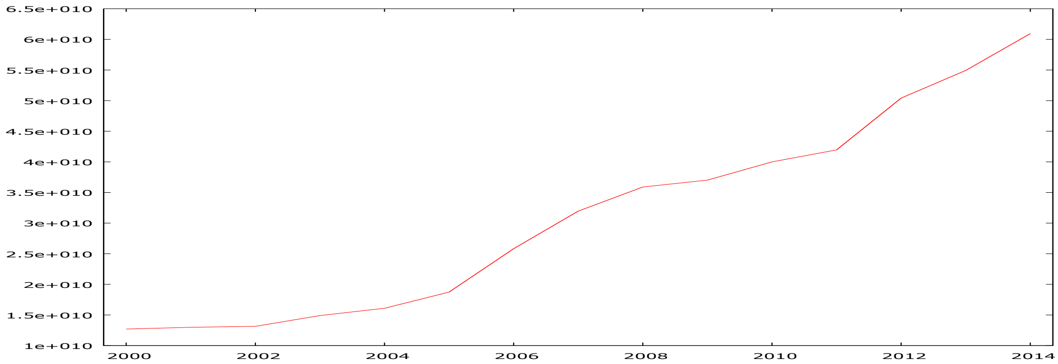


Figure 1.44 Market capitalisation of Kenya's listed companies (% of GDP)

Figure 1.45 Market capitalisation of listed companies (current US$)

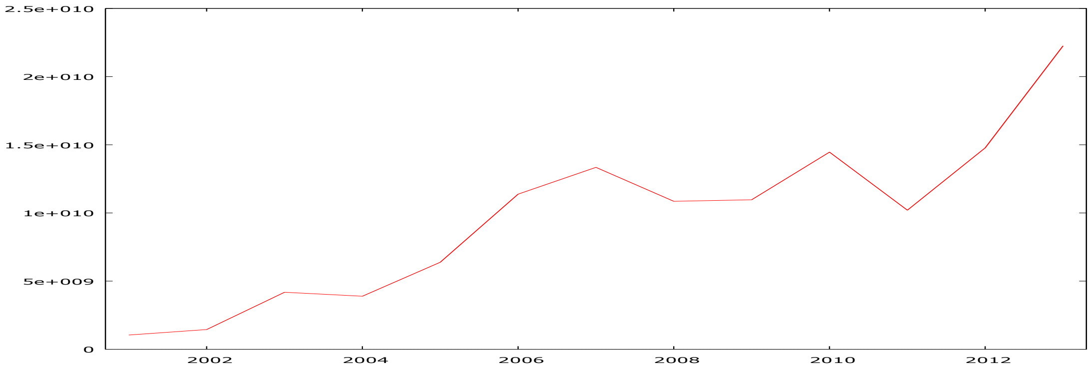


Table 1.12 Summary statistics of GDP growth, GDP (US$), market capitalisation to GDP (%) and market capitalisation in US$ for Kenya

Variable	Mean	Median	Minimum	Maximum
GDP growth (%)	4.39	5.10	0.23	8.40
GDP (US$)	31167000000	31958000000	12705000000	60937000000
Mkt cap/GDP (%)	29.33	29.62	8.05	44.06
Mkt cap (US$)	9629800000	10854000000	1045300000	22256000000
Variable	Std dev.	CV	Skewness	Ex. kurtosis
GDP growth (%)	2.46	0.56	−0.43	−0.79
GDP (US$)	16352000000	0.27	−0.36	−1.39
Mkt cap/GDP (%)	10.83	0.37	−0.62	−0.32
Mkt cap (US$)	6079200000	0.63	0.29	−0.43

The GDP growth for Kenya was a mean of 4.39% compared with 3.06% in Botswana and 4.14% in Egypt. The market capitalisation to GDP was 29.33% compared with Botswana (25.93%), South Africa (184.35%), Egypt (48.32%) and Morocco (53.95%).

1.7.2.4 Nigeria

The Nigerian Stock Exchange was founded in 1960 with trading commencing in 1961.[12] It is a registered company limited by guarantee, licensed under the Investments and Securities Act (ISA) and regulated by the Securities and Exchange Commission (SEC) of Nigeria. In 1984, the exchange launched an all-share index that reached the 1000 mark in 1992.

In 1996, the percentage pricing system was introduced (with 5% as the limit of the daily fluctuation band) and later that year the T+14 settlement/delivery period was abolished and a weekly settlement/delivery period introduced. In 1997, the Central Securities Clearing System Limited was commissioned, providing automated clearing, settlement, delivery and custodian services. In 1999, it transitioned to a fully automated trading system. In 2000, the week-long settlement/delivery period was replaced by the T+3 settlement/delivery period.

The figure below shows the weekly time-series trade price of the Nigerian Stock Exchange all share index

[12] Nigerian Stock Exchange - http://www.nse.com.ng/about-us/about-the-nse/notable-dates

Figure 1.46 Weekly time-series price of the Nigeria Stock Exchange all share index

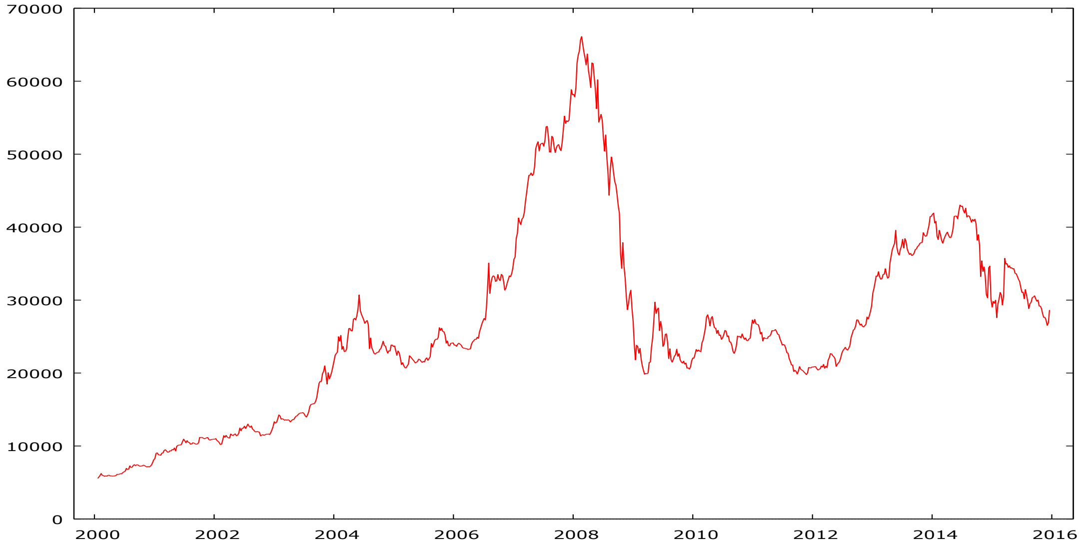


Figure 1.47 Weekly returns of the Nigerian Stock Exchange all share index

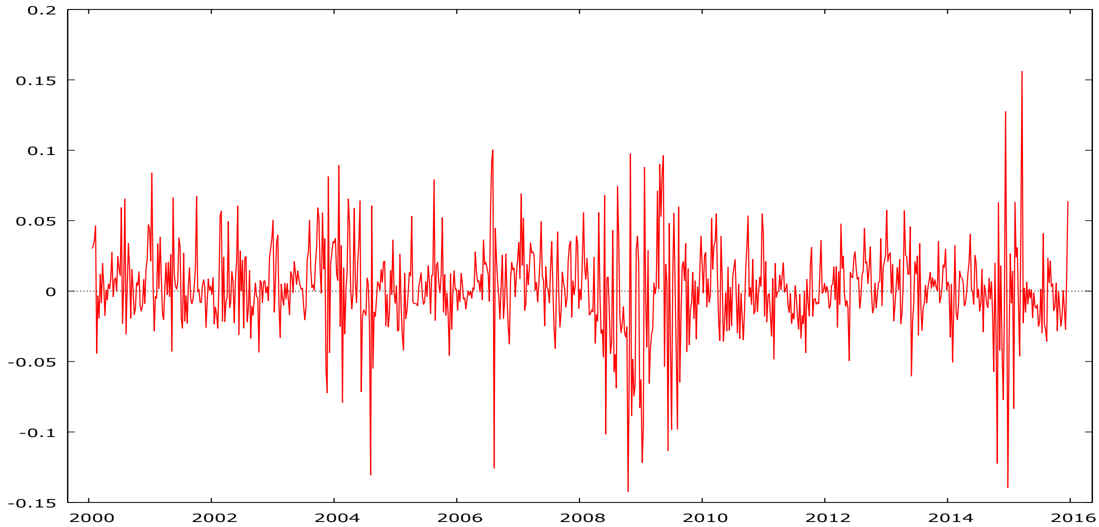


Table 1.13 Summary statistics of the returns on the Nigeria Stock Exchange all share index

Mean	Median	Minimum	Maximum
0.0020	0.0018	−0.1424	0.1562
Std dev	CV	Skewness	Ex. kurtosis
0.0311	15.480	−0.3087	3.7565

Figure 1.48 GDP growth for Nigeria

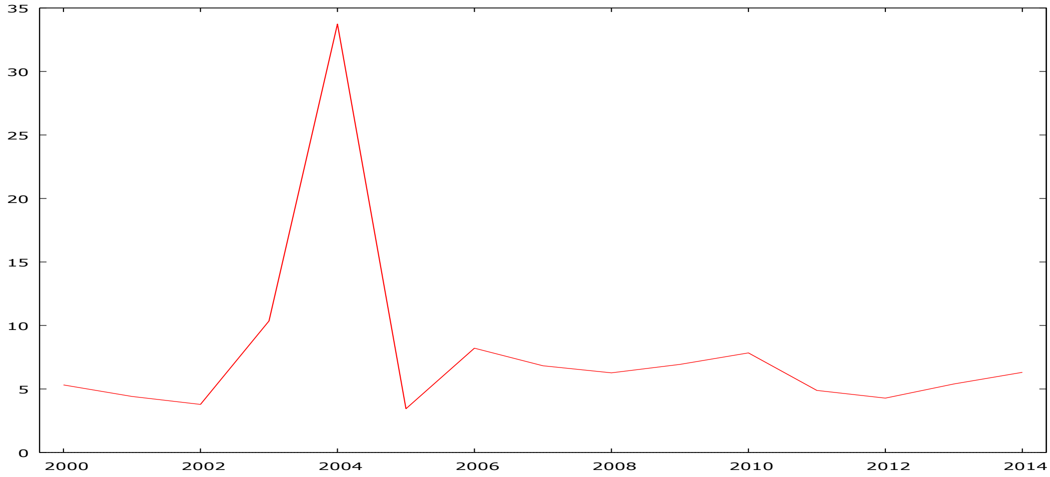


Figure 1.49 GDP for Nigeria in US$

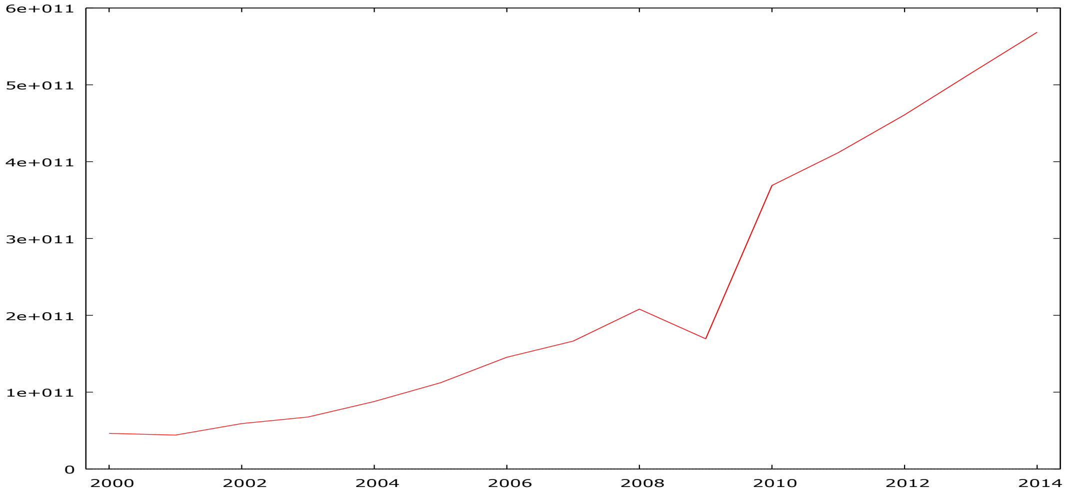


Figure 1.50 Market capitalisation of Nigeria's listed companies (% of GDP)

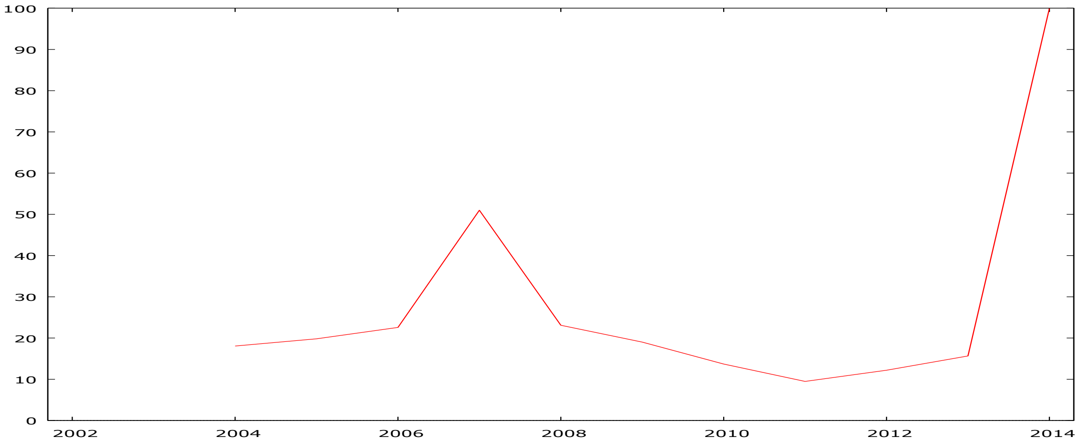


Figure 1.51 Market capitalisation of listed companies (current US$)

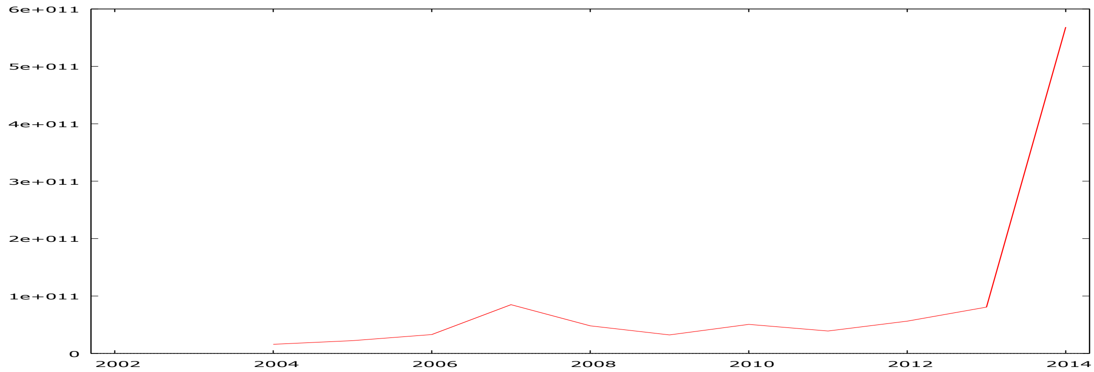


Table 1.14 Summary statistics of GDP growth, GDP (US$), market capitalisation to GDP (%) and market capitalisation in US$ for Nigeria

Variable	Mean	Median	Minimum	Maximum
GDP growth (%)	7.87	6.27	3.45	33.74
GDP (US$)	228800000000	166450000000	44138000000	568510000000
Mkt cap/GDP (%)	25.72	18.54	4.02	99.98
Mkt cap (US$)	86107000000	43545000000	2373900000	568400000000
Variable	Std dev.	CV	Skewness	Ex. kurtosis
GDP growth (%)	7.39	0.94	3.12	8.51
GDP (US$)	184140000000	0.80479	0.68	−1.08
Mkt cap/GDP (%)	26.06	1.01	2.17	3.70
Mkt cap (US$)	153810000000	1.79	2.88	6.61

Nigeria has the highest GDP growth all the countries within the sample with a mean GDP growth rate of 7.87%. However, the market capitalisation to GDP was quite low at 25.72% when compared with Kenya (29.33%), Botswana (25.93%), South Africa (184.35%), Egypt (48.32%) and Morocco (53.95%).

1.7.2.5 Tunisia

According to Hearn (2011), Tunisia's Bourse de Tunis was established in 1969, with electronic trading introduced in 1996. Settlement is fully G30-compliant,[13] with the trading system split into fixing and continuous systems. The fixing system handles the small and liquid securities with the continuous system trading from 09.00 to 14.10, but

[13]G30 refers to the Group of Thirty, which is the most influential body to encourage the standardisation and improvement in global securities administration.

from 08.30 to 12.10 during Ramadan. To attract listings, the bourse established an alternative market with relaxed regulations. This was also done to attract greater prominence in the financing of domestic businesses as, according to Zribi (2008), only 5% of new finance was raised through the exchange in 2007. According to Hearn (2011), the exchange has only 48 listings, which is rather small.

According to Bass (2015), the turn of the millennium saw Tunisia achieve a good rate of economic growth with exports of goods and services (especially tourism) reaching a high of 56% of GDP in 2008. However, due to the global financial crisis, the eurozone crisis and the Arab Spring movement (which started in Tunis in December 2010), the share has since declined.

The figure below shows the weekly time-series trade price of the TUNINDEX all share index

Figure 1.52 Weekly time-series price of the TUNINDEX all share index

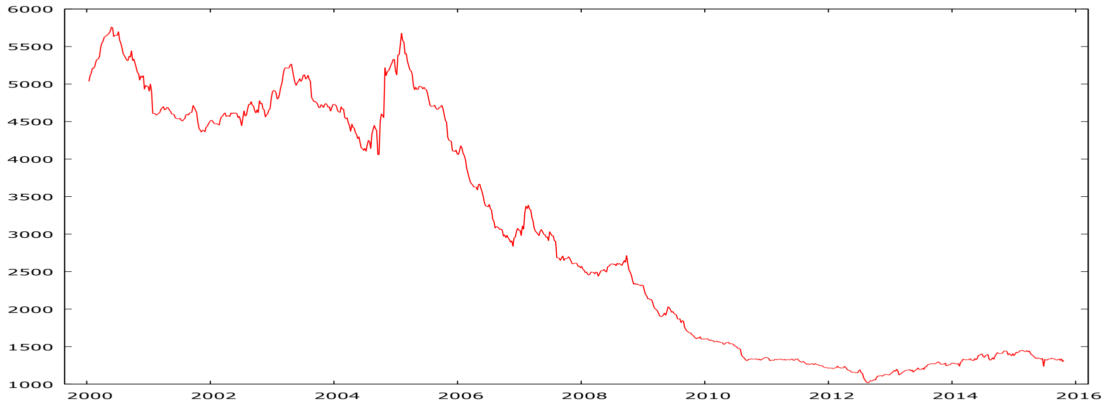


Figure 1.53 Weekly returns of the TUNINDEX all share index

Table 1.15 Summary statistics of the returns on the Tunisian Stock Exchange all share index

Mean	Median	Minimum	Maximum
0.0017	0.0013	−0.1363	0.0835
Std dev.	CV	Skewness	Ex. kurtosis
0.0156	9.0302	−0.6787	13.703

Figure 1.54 GDP growth for Tunisia

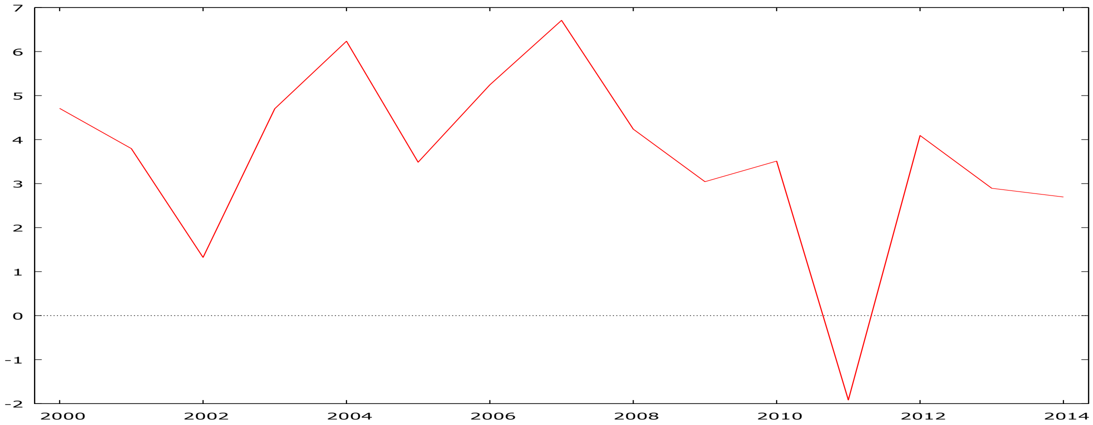


Figure 1.55 GDP in US$ for Tunisia

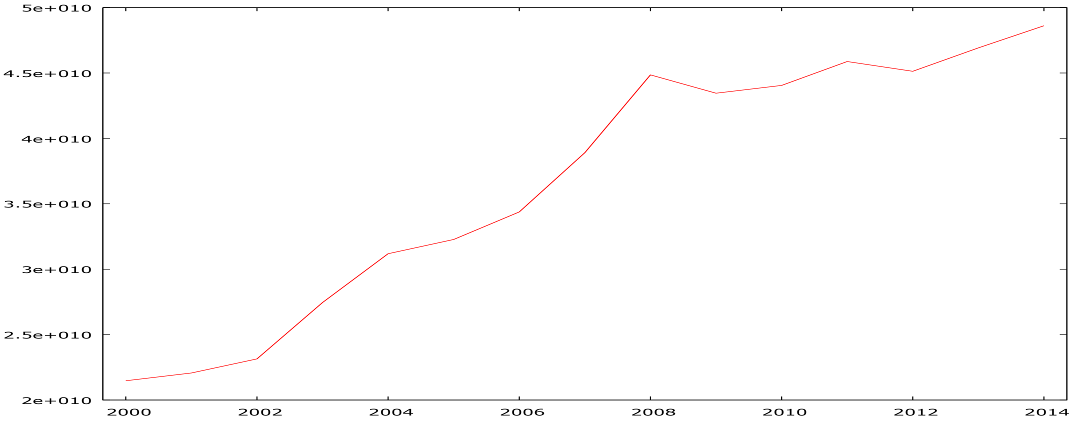


Figure 1.56 Total value to stocks traded (% of GDP) on the Tunisian market

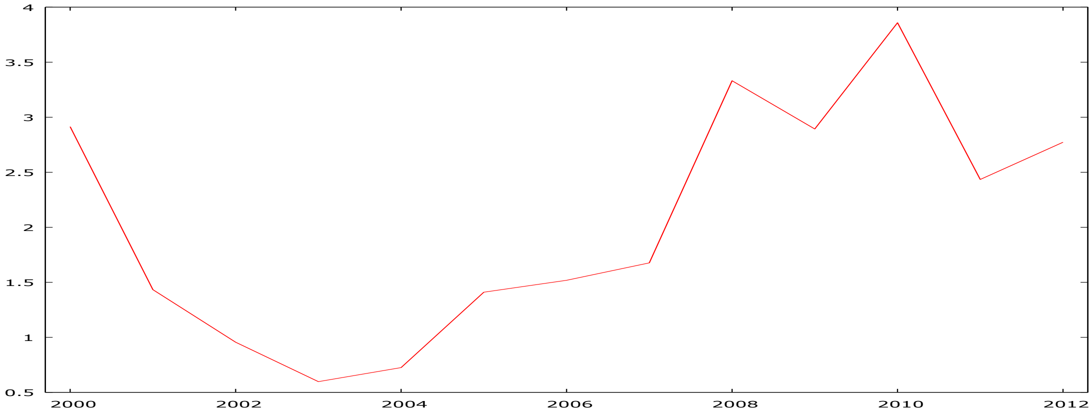


Figure 1.57 Market capitalisation of Tunisia's listed companies (% of GDP)

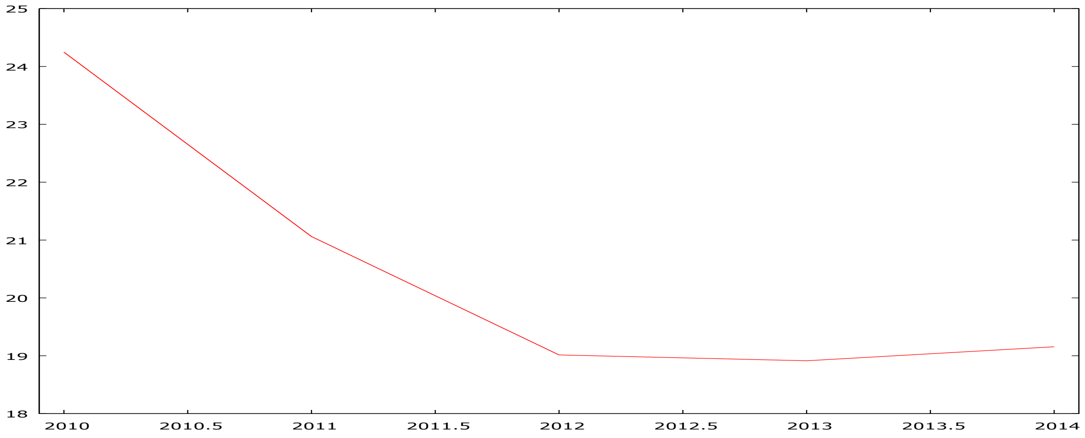


Figure 1.58 Market capitalisation of listed companies (current US$)

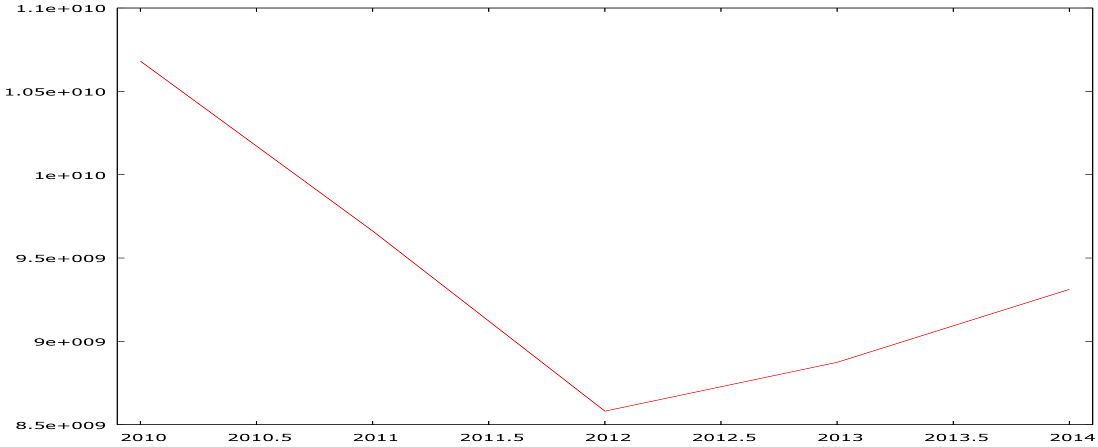


Table 1.16 Summary statistics of GDP growth, GDP (US$), stocks traded to GDP

Variable	Mean	Median	Minimum	Maximum
GDP growth (%)	3.65	3.80	−1.92	6.71
GDP (US$)	36652000000	38908000000	21473000000	48613000000
Stocks traded/GDP(%)	2.04	1.68	0.60	3.86
Mkt cap/GDP (%)	20.48	19.16	18.91	24.25
Mkt cap (US$)	9422200000	9312000000	8581300000	10681000000
Variable	Std dev.	CV	Skewness	Ex. kurtosis
GDP growth (%)	2.07	0.57	−1.13	1.77
GDP (US$)	9796000000	0.27	−0.36	−1.39
Stocks traded/GDP	1.05	0.52	0.20	−1.22
Mkt cap/GDP (%)	2.29	0.11	1.04	−0.53
Mkt cap (US$)	815820000	0.086586	0.64	−0.81

The average GDP growth for Tunisia over the period was 3.65% per year with a minimum of −1.92% and a maximum of 6.71% per year, respectively. This is higher than seen in South Africa (3.21%) but lower than GDP growth in Egypt (4.15%) and Morocco (4.37%). The average GDP (US$) was $36,652,000,000 with a minimum of $21,473,000,000 and a maximum of $48,613,000,000. Stocks traded were a mean of 2.04% of GDP, with a minimum and maximum value of 0.60% and 3.86%, respectively. This is significantly lower than the stocks traded-to-GDP ratio in the emerging African market. For example, the mean stocks traded-to-GDP ratio in South Africa was 89.35%, Egypt 18.99% and Morocco 11.75%.

The market capitalisation to GDP ratio was an average of 20.48%, which is significantly lower than reported in the South African market (184.35%), Egypt 48.32% and Morocco 59.95%. The minimum and maximum market capitalisation to GDP were 18.91% and 24.25%, respectively. The market capitalisation in the Tunisian stock market was an average of $9,422,200,000, with a minimum of $8,581,300,000 and a maximum of $10,681,000,000.

2 LITERATURE REVIEW

2.1 Introduction

Establishing the relationship between risk and expected return has become one of the most important areas in modern finance. The expected return from rational equity markets is solely determined by the underlying risk, hence many researchers have made efforts to identify factors that capture risk. The theory that has formed the bedrock of this effort is the capital asset pricing model (CAPM), which was developed in the early 1960s by William Sharpe (1964), Jack Treynor (1962), John Lintner (1965a, 1965b) and Jan Mossin (1966). As identified in Harvey (1991), most tests of this mean-variance efficiency of the world market have failed to reject the CAPM. However, most of these tests were carried out in developed markets and only a few in developing markets.

In analysing the distribution characteristics of emerging market returns, Bekaert et al. (1998) found that emerging equity markets have high volatility, low correlation with developed markets and, within the emerging markets, high, long-horizontal returns and predictability above and beyond what is found in developed market returns. They also indicate that the efficient frontier is pushed forward when emerging market returns are plugged into the standard Markowitz (1959) framework. This is because of a combination of low correlation and high expected return. They conclude that because emerging market returns cannot be completely characterised by the traditional mean-variance measures of the CAPM, application in these markets becomes problematic.

Most of the research on asset pricing has focused on the developed markets and some emerging markets, with very few studies on the African market. Hence this study will focus on identifying the factors that are important within the African market. This is very important given the severe illiquidity and thin trading problems identified in Allen, Otchere and Senbet, 2011. According to Pagano (1989), when markets are thin volatility increases along with the tendency for asset prices to react adversely to the orders of traders. This can lead to instability in the beta, which is contrary to the assumption of the static CAPM, hence conditional information may play an important role in explaining excess returns in the African stock market.

Others believe that the behaviour of stock-market returns does not conform to the frequently assumed normal distribution as stated in Harvey and Siddiqui (1999, 2000). This is due to non-stationarity, which is most severe in the African market. This results from changes in the level of market integration, significant non-economic factors such as political factors, re-emerging and survivorship bias in data, and the evolution from an emerging/frontier market towards a mature market.

The literature around asset pricing is vast; to develop a framework within which this research will be conducted, Section 2.2 will review the historical development of the CAPM, which will further investigate portfolio theory and the separation theorem in Section 2.2.1, rational expectation, non-correlated trading and arbitrage in Section 2.2.2, the efficient market hypothesis in Section 2.2.3, empirical tests on the CAPM in Section 2.2.4, the three-factor model and other tests of the CAPM in Section 2.2.5 and the four-factor model in Section 2.2.6. Fuller details of the methodologies are discussed in Chapter 3.

Given the relative underdevelopment of the African market, I expect some irrationality in investors' decision-making, hence Section 2.2.7 will analyse the literature on the impact of behavioural finance on asset pricing. To evaluate the impact of the characteristics of surveyed markets on the performance of the CAPM and multifactor models, literature on the performance of the CAPM in developing versus developed economies are analysed in Section 2.3.

Because of the impact of illiquidity and thin trading on asset-pricing models, Section 2.4 reviews the literature on liquidity and its potential importance in the African market. Section 2.5 investigates the impact of market segmentation in the African market and Section 2.6 the potential impact of contagion. Structural breaks in the data are discussed in Section 2.7 and, following the possible presence of structural breaks, I explore the literature on conditional asset pricing in Section 2.8, with a view to identifying gaps in the literature.

Other very important aspects of asset pricing are reviewed as well: higher moments in Section 2.9, the risk-free rate in Section 2.10 and the effect of survivorship bias in Section 2.11, with the gaps in the literature identified in the conclusion in Section 2.12.

The major issues regarding asset pricing that relate to the African market as presented in the literature are tabulated below.

Table 2.1 Major areas of research potentially important in the African market.

Section	Important issues	Important papers
2.2.4.1	Risk premium	Miller and Scholes (1972)
		Black, Jensen and Scholes (1972)
		Blume and Friend (1973)
		Fama and MacBeth (1973)
2.2.4.2	Beta and expected return	Roll (1977)
		Reinganum (1981)
		Stambaugh (1982)
		Lakonishok and Shapiro (1986)
2.2.5	Three-factor model	Fama and French (1992, 1996)
2.2.6	Four-factor model and momentum	Jagadeesh and Titman (1993)
		Carhart (1997)
2.2.7	Behavioural finance	De Bondt and Thaler (1985)
		Chopra, Lakonishok and Ritter (1992)
		Blume, Easley and O'Hara (1994)
		Hirshleifer and Shumway (2003)
2.3	Characteristics of the African market	Ekechi (1989)
		Kenny and Moss (1998)
		Omran (2007)
		Senbet and Otchere (2010)
		Allen, Otchere and Senbet (2011)
2.4	Liquidity effect	Pástor and Stambaugh (2003)
		Correia and Uliana (2004)
		Martinez et al. (2005)
		Lesmond (2005)
		Liu (2006)
		Hearn and Piesse (2009)
2.6	Contagion	Claessens and Forbs (2004)
		Bekaert, Harvey and Ng (2005)
		Boamah (2014)

		Ahnert and Bertsch (2014)
2.7	Structural breaks	Faboozi and Francis (1978)
		Garcia and Ghysels (1998)
		Harvey and Lumsdaine (2002)
		Bai and Perron (2003)
		Merton (1973)
2.8	Conditional CAPM, intertemporal CAPM, bull and bear beta	Jagannathan and Wang (1996)
		Zhang (2005)
		Lusting and Van Neiuwerburgh (2005)
		Lewellen and Nagel (2006)
		Chong, Halcoussis and Phillips (2012)
2.9	Higher-order moments	Bekaert et al. (1998)
		Hwang and Satchell (1999)
		Siddiqui (1999, 2000)
		Kim and White (2004)
2.10	Risk-free rate	Collins and Abrahamson (2006)
		Hearn and Piesse (2009)
2.11	Survivorship bias	Boynton and Oppenheimer (2006).
		Rohleder et al. (2011)

2.2 Historical overview of the CAPM

Before the CAPM, Harry Markowitz (1959) developed the portfolio theory, which assumes that investors are averse to risk and that they are only interested in the mean and variance of their portfolio, which is selected at time $t-1$ and produces a stochastic return at t. Following this, Fama and French (2004) highlight that investors choose a mean-variance-efficient portfolio, which, given expected return, should minimise the variance of the portfolio return and, given variance, should maximise expected return.

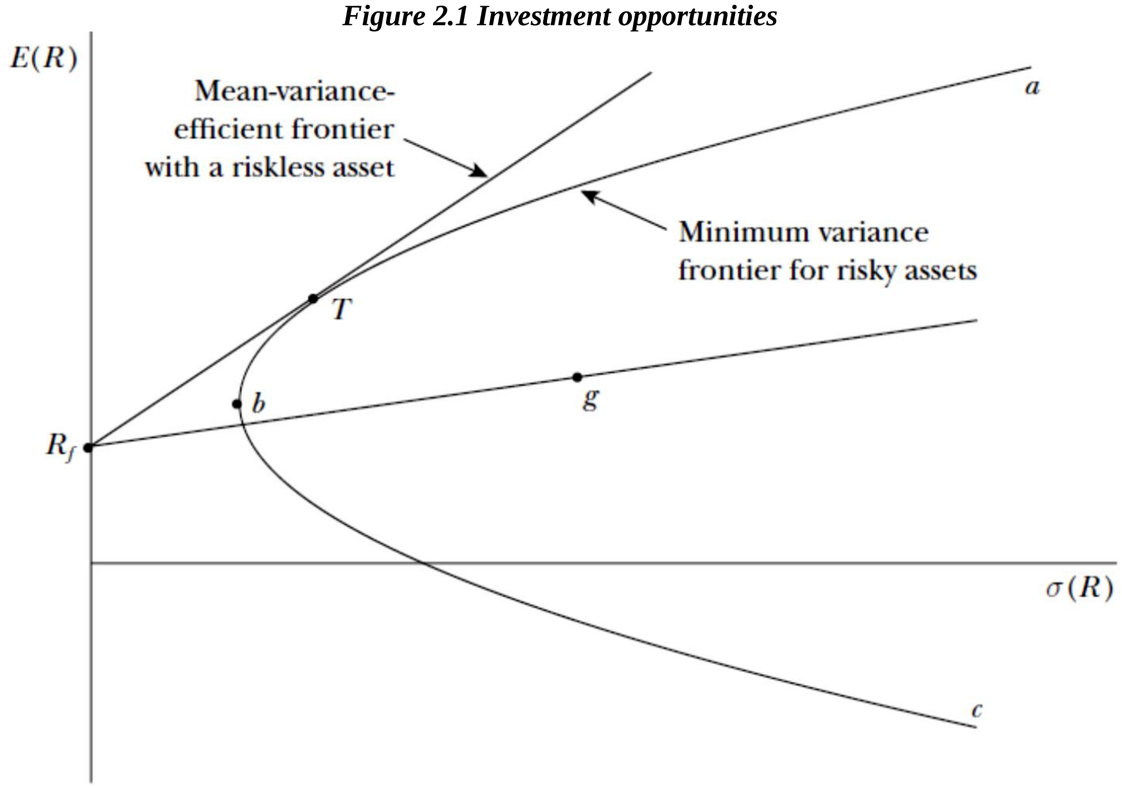
Based on the algebraic conditions established in the Markowitz portfolio model, the CAPM establishes a testable prediction about the relation between expected return and risk. For asset prices to clear the market of all assets, the CAPM identifies a portfolio that must be efficient. Identifying this mean-variance-efficient portfolio depends on certain assumptions regarding the portfolio model, as disclosed by Sharpe (1964) and Lintner (1965). One of the assumptions, as stated in Perold (2004), is that investors can borrow as well as lend at the risk-free rate no matter what the amount borrowed or lent is. Perold (2004) defines a risk-free rate as an instrument that pays a fixed, real return and is default-free. An example of a risk-free instrument in this case is a US Treasury bill or a US Treasury inflation-protected instrument (TIPS). Another assumption relates to the homogeneous expectations or beliefs of investors. According to Bodie et al. (2011), this assumption of the CAPM implies that all investors share the same economic view of the world and analyse securities in the same way, resulting in identical estimates of the probability distribution of asset return, i.e. a homogeneous list of inputs for any set of security prices to feed into the Markowitz portfolio model. They go on to highlight that with the risk-free interest rate, and given a set of security prices, all investors generate the efficient frontier and the unique optimal risky portfolio using the same expected return and covariance matrix of security return.

The third assumption is that investors are risk-averse and evaluate their investment portfolios solely in terms of standard deviation and expected return measured over a single holding period; hence they all use the Markowitz portfolio selection model. The fourth assumption refers to the perfection of the market in the following sense: all assets are infinitely desirable; there are no transaction costs, no taxes, no short-selling; and information is costless and available to everyone. The fifth assumption describes the wealth holding of investors. It states that the wealth of each individual investor amid the many investors is small compared to the total investor wealth. The assumption of perfect competition in microeconomics holds, where investors act as though security prices are not affected by their own trades, hence investors are price-takers.

And, lastly, a universe of publicly traded financial assets constrains investments. This assumption limits traded assets to financial assets such as bonds, stocks and risk-free borrowing and lending arrangements, while excluding investments in non-traded assets such as private enterprise, human capital and government-funded assets such as international airports.

Using the assumptions identified above, the logic of the CAPM as stated in Fama and French (2004) can be described as in Figure 2.1 below.

Figure 2.1 Investment opportunities



The vertical axis measures the expected return and the horizontal axis shows the standard deviation of portfolio returns, which measures the risk of the portfolio. The abc curve outlines combinations of risk and expected return for risky asset portfolios at various levels of expected return for which variance is minimised (lending and borrowing at the risk-free rate is not included). The trade-off between expected return and risk is apparent for minimum variance portfolios, as shown in Figure 2.1; investors desiring a particular level of expected return must be willing to accept the corresponding risk of the portfolio. For example, investors who desire a high level of expected return, say at point a in the graph, must be willing to accept the high level of risk associated with a. Conversely, point T presents an intermediate level of expected return with lower volatility. Portfolio b and those above it along the abc curve are the only mean-variance-efficient portfolios when there is not risk-free borrowing or lending. This is because, given their return variances, these portfolios maximise expected return.

The efficient set is turned into a straight line with the addition of risk-free borrowing and lending. Consider an investor who invests x proportion of his funds in a security classed as risk-free and $1 - x$ in portfolio g. Given a risk-free investment of all funds, i.e. loaned out at an interest equal to the risk-free rate, the result is a portfolio with a risk-free rate of return and zero variance, i.e. the point R_f in Figure 2.1. Combining positive investment in g and risk-free lending can be seen on a straight line between R_f and g. On the right of g along the straight line are borrowings at the risk-free rate with the proceeds from the borrowing used to increase investment in portfolio g. That is to say that portfolios that combine risky portfolio g with risk-free borrowing or lending plot along a straight line from R_f through g.

A mean-variance-efficient portfolio can be obtained with risk-free borrowing and lending by drawing a line from R_f to the tangency portfolio T, to the left as far as possible. It thus becomes clear that all efficient portfolios are combinations of the risk-free asset and a single risky tangency portfolio, T. This was highlighted in the works of James Tobin (1958), who showed that the efficient frontier simplifies in an important way when investors can borrow as well as lend at the risk-free rate. This is the key to the separation theorem, which will be discussed in more detail later in the chapter.

Combining this with the assumptions of the CAPM, the picture becomes a whole lot clearer; investors have complete agreement on the distribution of returns, hence they see the same opportunity and combine the same risky portfolio T with risk-free lending or borrowing. This portfolio T must be a value-weighted portfolio of risky assets since all investors hold that same portfolio. The market portfolio that is denoted as M, which represents each risky asset's weight in the tangency portfolio, must be the total market value of all outstanding units of the asset divided by the total market value of all risky assets. Also, the risk-free rate must be set to clear the market of risk-free borrowing and lending, along with prices of risky assets.

The assumptions of the CAPM imply that if the market portfolio M must be on the minimum variance asset for the market to clear, the algebraic relation for the market portfolio must follow that of the minimum variance portfolio. Specifically, for N risky assets,

(M minimum variance condition)

$$E(R_i) = E(R_{ZM}) + [E(R_M) - E(R_{ZM})]\beta_{iM}, i = 1, \ldots, N. (2.1)$$

where $E(R_i)$ and β_{iM} are the expected return on i the market beta of i respectively, where

(market beta) $\beta_{iM} = \frac{cov(R_i, R_M)}{\sigma^2(R_M)}$ (2.2)

as the covariance of its return with the market return divided by the variance of the market return.

The expected return on assets that are uncorrelated with the market (those that have market betas equal to zero) is denoted by $E(R_{ZM})$, the first term on the right-hand side of the minimum variance condition. The risk premium that is the market beta of asset i, β_{iM}, times the premium per unit beta, which is the expected market return, $E(R_M)$, minus $E(R_{ZM})$. This is the second term of the minimum variance condition.

A correct and indeed common interpretation of the beta is that it measures the sensitivity of the asset's return to variation in the market return. This is because the slope in the regression of the return of asset i on the market return is the market beta β_{iM}. However, the beta can also be interpreted differently and more in line with Harry Markowitz's portfolio model upon which the CAPM is established. The risk of the market portfolio is the weighted average of the covariance risks of the assets in M $[cov(R_i, R_M)]$, which is measured by the variance of its return $[\sigma^2(R_M)]$. That is to say that β_{iM} is the covariance risk of asset i in M measured relative to the average covariance risk of assets.

The expected return on a zero-beta asset $E(R_{ZM})$ is nailed down using the risk-free borrowing and lending assumption. The expected return on an asset is uncorrelated with the market return when the average of the assets covariance with the return on other assets just offsets the variance of the asset's return. In the market portfolio, this risky asset is riskless as it contributes nothing to the variance of the market return. The expected return on assets that are uncorrelated with the market $E(R_{ZM})$, must equal the risk-free rate, R_f, when there is risk-free borrowing and lending. The familiar Sharpe-Lintner CAPM equation of the relationship between return and beta results from this.

(Sharpe-Lintner CAPM)

$$E(R_i) = R_f + [E(R_M) - R_f]\beta_{iM}, i = 1, \ldots, N. (2.3)$$

Perold (2004) highlights that these assumptions of the CAPM are highly simplified, which seems fairly obvious, but they are necessary to obtain the CAPM in its basic form. Relating to the assumption of unrestricted risk-free borrowing and lending, Fischer Black (1972) insists that is it unrealistic and thus developed a version of the CAPM without risk-free borrowing or lending. His results show that allowing unrestricted short sales of risky assets does not refute the key result of the CAPM – that the market portfolio is mean-variance-efficient. Looking back at Figure 2.1, if there were no risk-free asset, investors would pick portfolios along a to b, which is the mean-variance-efficient frontier. The market portfolio is formed through market clearing prices, as the weight of the aggregate invested wealth relating to investors in relation to the market portfolio. Thus, a portfolio of the efficient portfolios chosen by investors is the market portfolio. With unrestricted short-selling of risky assets, portfolios made up of efficient portfolios are themselves efficient.

Hence, the minimum variance condition for M given above holds as the market portfolio is efficient. It has the attributes of the Black CAPM.

The interpretations in relation to the expected return on assets that are uncorrelated with the market (those that have market betas equal to zero), denoted by $E(R_{ZM})$ constitute the only difference between the Black and the Sharpe-Lintner versions of the CAPM. The Sharpe-Lintner version of the CAPM highlights that $E(R_{ZM})$ must be the R_f which is the risk-free rate, and $E(R_M) - R_f$ is the premium over one unit of beta risk. In contrast, the Black CAPM insists that $E(R_{ZM})$ must be less than the expected market return, so the premium for beta is positive.

Both the assumptions of unrestricted risk-free borrowing and lending and that short-selling is unrestricted are unrealistic. Hence, portfolios made up of efficient portfolios will not be typically efficient if there is no risk-free asset and no short-selling of risky assets, as stated in the algebra of portfolio efficiency. If short-selling is not allowed and there is no risk-free asset, mean-variance investors will still choose the efficient portfolios. But this means that the portfolio of the efficient portfolios, which is the market portfolio chosen by investors, is not typically efficient and the expected return and market beta relation of the CAPM is lost. The predictions regarding expected return and betas with regards to other efficient portfolios cannot be ruled out if theory can specify the efficient portfolios required if the market is to clear. But this has proven impossible so far.

It can then be deduced that many unrealistic assumptions form the basis for the efficiency of the market portfolio. But this is not unusual for interesting models, which is why they must be tested against data. This review will critically analyse the major area of research investigating the portfolio theory and asset pricing.

2.2.1 Portfolio theory and the separation theorem

In contrast to Markowitz's contribution, which may be viewed as microeconomic, Tobin (1958) addressed the liquidity preference problem largely referred to as a standard Keynesian macroeconomic problem. The aggregative function was proposed by Keynes without a formal deviation. Tobin (1958) derives the economy's liquidity preference by developing a theory that explains the behaviour of the decision-making units of the economy. One may wonder what the connection between liquidity preference and portfolio theory is. Three motives for holding cash are identified by Keynes and these are transactions, precautionary and speculative. While income determines the transactions and precautionary motives, the amount of cash held for speculative motive was influenced by the rate of interest. The foundation for Tobin's interest elasticity of the liquidity preference derives its strong theoretical foundation from this speculative motive of investors, as detailed in Constantinides and Malliaris (1995). Tobin considered only cash and consoles (government securities) as the assets available to an investor, as he wanted to explain the demand for cash.

He highlights that the higher the proportion of investment in console balance available to an investor, the more risk the investor assumes. At the same time, increasing the proportion of consoles also increases his expected return. As Tobin states, the investor is assumed to have preferences between expected return and risk that can be represented by a field of indifference curves. Plausibly, for some investors, *risk-lovers*, these indifferent curves have negative slopes. These investors are willing to accept lower expected returns in order to have the chance of unusually high capital gains afforded by high values of risk.

Risk-averters, on the other hand, will not be satisfied to accept more risk unless they can also expect greater expected returns. Their indifference curve will be positively sloped. According to Tobin (1958), there are two kinds of risk-averters; the first, which he called *diversifiers*, are those whose indifference curves are concave upwards. The second group he called *plungers*, which are those whose indifference curves are also sloping upwards, but either linear or convex.

As stated in Elton and Gruber (1997), when the investor has access to riskless assets, the choice of optimum portfolio of risky assets is unequivocal and independent of the investor's expected returns or variance. This is the principle of the separation theorem. The implications of the separation theorem include the facilitation of calculation where the portfolio problem can be restated as a problem of finding the tangency portfolio to a line passing through the riskless asset in expected return standard deviation space, as highlighted in Elton and Gruber (1997). The portfolio that maximises the ratio of expected return minus the return on the riskless asset to the standard deviation is the tangency portfolio. According to Tobin (1958), nothing changes if there are many risky assets. This is because, as stated in Constantinides and Malliaris (1995), the risky assets can be viewed as a single composite asset (mutual fund) and investors find it optimal to combine their cash with a specific portfolio of risky assets.

This connects the separation theorem to the mutual fund theorem, which states that the desired portfolio of investors can be obtained by mixing two mutual funds: one representing the tangency portfolio and one made up of the riskless asset. Another implication is that other assumptions will then be taken into consideration, for example more funds and new types of funds will enter the decision set. Suppose that all investors choose to invest in mean-variance-efficient portfolios due to restrictions in utility functions, and they choose specific proportions of two distinct mean-variance efficient portfolios that generate all the others. The two specific proportions can be used to generate the market portfolio, which is the wealth-weighted sum of the portfolio holding of all investors. According to Constantinides and Malliaris (1995), this implies that the market portfolio is also mean-variance-efficient. This was the cornerstone of Black's (1972) development of the CAPM.

Before the work of Black (1972), Sharpe (1964) identified that most authors have used models similar to that proposed by Tobin to derive corresponding conclusions about individual investor behaviour. Sharpe, however, highlighted that Hicks (1962) identified more explicitly the nature of the conditions under which the process of investment choice can be dichotomised. Sharpe also identified the work of Gordon and Gangpolli (1962), which included a rigorous proof in the context of a choice among lotteries. Sharpe went further to state that no author has attempted to extend models of investor behaviour to construct a market equilibrium theory of asset prices under conditions of risk. Sharpe (1962) provided this extension and identified that such extension provides a theory with implications consistent with the assertions of traditional financial theory.

2.2.2 Rational expectation, non-correlated trading and arbitrage

When diverse and asymmetric information is available to agents in speculative markets, equilibrium prices will normally contain information beyond that held by each agent originally. According to Admati (1985), "this observation together with the assumption that agents make statistically correct inferences based on all the information they possess, including current prices, leads to the notion of rational expectations equilibrium where equilibrium prices affect agents' behaviour both by entering their budget constraints and by influencing their beliefs and predictions". As stated in Admati (1985), most of the development within the literature on rational expectation has been concerned with fully revealing equilibria, within which we observe that in equilibrium, information asymmetry that may exist disappear.

As seen in Milgrom (1981), when each trader is privy to their own information that is private, or acquire information at a cost, their options may be significantly different when compared to the case where information is public. It may be possible for a trader to infer information from the terms of trade he is offered or from any observations he makes concerning the behaviour of other traders. Milgrom (1981), however, identifies that the existing rational expectations equilibrium models are defective. Admati (1985) also highlights that the notion of fully revealing rational expectations equilibrium has proved problematic, both conceptually and empirically. This view was also expressed in Anderson and Ross (1985) and Grossman (1981). Admati (1985) did, however, identify that most of the problems associated with fully revealing equilibria are resolved if, because of some noise, agents are not able to extract all relevant information from prices. Noisy rational expectations models allow diversity of beliefs to be sustained in equilibrium where price information is being utilised optimally.

Grossman and Stiglitz (1980) indicate that within this competitive equilibrium, arbitrage profits are eliminated. They do, however, indicate that it is not possible for the economy to always be in equilibrium. Hence the assumption that all markets, including that for information, are always in equilibrium and always perfectly arbitraged is inconsistent when arbitrage is costly. Drake and Fabozzi (2010) do, however, identify that arbitrageurs profit without risk. However, such opportunities are rare in financial markets. They also identify that less obvious arbitrage opportunities exist in situations where a package of assets can produce a payoff (that is, expected return) identical to an asset that is priced differently. This arbitrage relies on a fundamental principle of finance, the law of one price, which states that a given asset must have the same price regardless of the means by which one goes about creating that asset.

When a situation is discovered whereby the price of the package of assets differs from that of an asset with the same payoff, rational investors will trade these assets in such a way as to restore price equilibrium. Following on, the arbitrage pricing theory believes that this arbitrage mechanism is possible and is founded on the fact that an arbitrage transaction does not expose the investor to any adverse movement in the market price of the asset in the transaction. However, if the market is efficient, there should not be consistent arbitrage opportunities as identified within the efficient market hypothesis, which is discussed below.

2.2.3 Efficient market hypothesis (EMH)

"A blindfolded chimpanzee throwing darts at the stock pages could select a portfolio that would do as well as the experts" - Burton G. Malkiel, 1973, p 4. (A Random Walk Down Wall Street).

Although the quote was made largely in jest, the analogy is to throw a towel over the stock pages and simply buy an index fund where the index holds all the stocks that constitute the broader stock market. The earliest form of the efficient market hypothesis appeared as the random walk theory (Bachelier, 1964). In the 1960s, the theory was confirmed empirically, as seen in Cootner (1964) and many more times since. The EMH is based on the overarching logic that were returns forecastable, many investors would use them to generate unlimited profits. However, the behaviour of these investors will induce returns that obey the EMH, and should this not happen, there would exist a "money machine" producing unlimited wealth. This contrasts with the expectation from a stable economy.

In defining market efficiency, Jensen (1978) identified a market as efficient in respect of information set θ_t if it is impossible to make economic profits by trading based on information set θ_t. A similar definition was provided in Timmermann and Granger (2004). Malkiel (1992) identified an efficient capital market as one where all relevant information in fully and correctly reflected in security prices. This implies that it is impossible to make economic profits by trading based on information set θ_t. Hence the market is said to be efficient with respect to information set θ_t, if security prices would be unaffected by revealing that information to all market participants. Timmermann and Granger (2004) highlight three points of emphasis: the first relates to the importance of the information set used in the test θ_t; the second relates to the ability to exploit this information in a trading strategy; and the third relates to use of economic profit as the yardstick. Economic profit here relates to profits that are risk-adjusted and net of transaction costs.

The information sets in use within most EMH literature are categorised based on the set of variables contained in the information set θ_t as seen in Roberts (1967) and Fama (1970). When θ_t comprises current and past asset prices, as well as variables such as trading volume and possibly dividends, as revealed in Timmermann and Granger (2004), the EMH is being tested in its weak form. When θ_t is expanded to include information that is publicly available, the EMH is being tested in its semi-strong form. When θ_t is expanded to include information that is both publicly and privately available, the EMH is being tested in its strong form. Most studies in the literature test EMH in its weak or semi-strong form because private information is more expensive to acquire and harder to measure. The strong form can, however, be tested indirectly as identified in Timmermann and Granger (2004) by considering the performance of fund managers and testing if they earn profits net of risk premiums when the cost of private information has been accounted for.

In recent years, many financial economists have started questioning the EMH as it has seemed that there have been some instances where prices failed, ex-post, to reflect available information, as identified in Malkiel (2005). There have also been large-scale periods of irrationality as seen during the internet bubbles of the early 1990s and early 2000, and also the recent 2008 financial crisis. According to Robert Shiller (2000), in his book, *Irrational Exuberance*, the EMH should be rejected. Others highlight that the stock prices are, to a large extent, predictable on the basis of either valuation metrics such as price-to-earnings ratio and dividend yield or based on past returns, as seen in Fama and French (1988), Campbell and Shiller (1988a,b), Lo and MacKinlay (1999) and De Bondt and Thaler (1995).

However, there have been doubts cast on the robustness of many of the predictable patterns that have been developed, as seen in Fama (1998) and Malkiel (2003). Dimson and Marsh (1999) highlight the disappearance of the small-cap premium in the UK stock market after it became publicly known. Bossaert and Hillioin (1999) find out-of-sample disappearance of in-sample predictability of monthly stock returns in a variety of international stock markets. Aiolfi and Favero (2002) also reported the disappearance of the predictability in US stocks, which had been documented in earlier studies, in the 1990s. Sullivan, Timmermann and White (1999) found the technical trading rules that historically generate excess returns to have broken down after 1986. However, and rather fascinatingly, Brook, Lakonishok and LeBaron (1992) found technical trading rules to be profitable in 1986.

The investigation of market efficiency in the African market had previously received very little attention due to data paucity. Those who pioneered efficient markets research in the African market include Samuels and Yacout (1981) and Parkinson (1984) using autocorrelation tests, who, however, offered conflicting results, as identified in Ntim et al (2011). While Samuels and Yacout could not reject weak-form efficiency in 21 listed Nigerian firms, Parkinson rejects weak-form efficiency in 30 listed Kenyan firms. However, later studies in the Kenyan market, as seen in Dickinson and Muragu (1994), found evidence of weak-form efficiency. In investigating weak-form efficiency using the partial-autocorrelation test, Magnusson and Wydick (2002) found weak-form efficiency in six out of eight African stock markets. The weak-form efficient markets are Botswana, Cote d'Ivoire, Kenya, Mauritius, Nigeria and South Africa, while Ghana and Zimbabwe were not weak-form efficient.

Appiah-Kusi and Menya (2003) investigated weak-form efficiency in 11 African stock markets using an EGARCH-M model. Their result demonstrates weak-form efficiency for Egypt, Kenya, Morocco, Mauritius and Zimbabwe, while Botswana, Ghana, Ivory Coast, Nigeria, South Africa and Swaziland were not efficient. Jefferis and Smith (2005) also used a GARCH model to investigate serial dependence in eight African stock markets, but found only South Africa to be weak-form efficient. In using a robust, non-parametric, variance-ratio test in addition to its parametric form, Ntim, Opong and Danbolt (2007) found the Ghana stock market to be weak-form inefficient. Unlike previous studies, the findings are robust to thin trading, sub-sample periods and choice of dataset.

Ntim et al (2011) investigated 24 African continent-wide stock indices and eight individual stock-price indices. They found improvements in informational efficiency within the countrywide indices over the individual national stock indices, notwithstanding the test statistic used. They also found better improvement in efficiency for sector-based indices than size indices. They conclude that no individual national index is weak-form efficient, while 80% of African sectorial indices are weak-form efficient even when the robust Wright (2000) non-parametric, variance-ratio tests are used. Ntim (2012) documents similar findings. Following the evidence highlighted, this study will employ African continent-wide stock indices, but on a regional basis, to establish potential difference in returns behaviour within the regions.

2.2.4 Empirical tests on the CAPM

As stated in Fama and French (2004), tests of the CAPM usually take the form of examining the relationship between the market beta and expected return implied by the CAPM model in three distinct ways. The first implication of the CAPM is that expected returns on the market portfolio are greater than the expected return on assets, where the asset returns are uncorrelated with the market return, indicating the beta premium is positive. The second implication is that no other variable has marginal explanatory power as expected returns on all assets are linearly related to their betas. The last implication is that expected returns of uncorrelated assets are the risk-free rate, while the expected market return minus the risk-free rate is the beta premium. Fama and French (2004) also note that most tests of the CAPM use either time-series or cross-sectional regression.

2.2.4.1 Risk premium tests

Miller and Scholes (1972) and Black, Jensen and Scholes (1972) examining stock in the US between 1937 and 1965 found that low-beta stocks did better than the CAPM predicts, while high-beta stocks performed worse. They found that the slope of the line that relates the expected return to risk as stated in the CAPM is higher than the line relating average return and risk in their sample. In other words, and as explained in Miller and Scholes (1972), β is the systematic determinant of α on individual assets, but that low-beta stocks tend to have positive α's and high-beta assets tend to have negative α's.

Fama and MacBeth (1973) and Blume and Friend (1973) found that the estimated relationship between average excess return and beta is too flat and the intercept is positive.

In articulating the research on the tests of the CAPM, Fama and French (2004) highlight the CAPM's approach in regressing a cross-section of average asset returns on estimates of asset beta, where the intercept is the risk-free rate R_f and the coefficient of beta the risk premium $E(R_M) - R_f$. Furthermore, they identify two problems: the imprecise nature of estimates of beta for individual assets and, secondly, common sources of variation on the regression residuals.

Black, Jensen and Scholes (1972) indicate that the expected return on a security can be represented by a two-factor model such as

$$E(\tilde{r}_j) = E(\tilde{r}_z)(1 - \beta_j) + E(\tilde{r}_M)\beta_j \quad (2.4)$$

Where r is total return, $E(\tilde{r}_z)$ is the expected return on the second factor, which is referred to as the beta factor because it has a coefficient that is a function of the assets beta. Black, Jensen and Scholes (1972) showed that when the riskless borrowing and lending assumption is relaxed, the asset-pricing model provides that, in equilibrium, the expected return on an asset is given by Equation 2.4 above. These findings defined $\tilde{r}_z$ explicitly as the return on a zero covariance portfolio with the market portfolio return $\tilde{r}_M$. These findings are identical to those of Mayers (1972), who established the model incorporating non-marketable assets in an equilibrium model and has shown that the basic linear relation of the traditional model is unchanged, but the constant term will be non-zero and will not be equal to $E(R_M)$.

To improve the precision of estimated betas, Black, Jensen and Scholes (1972), Friend and Blume (1970), and Blume (1970) have all suggested the use of portfolios instead of individual securities. On the other hand, Fama and MacBeth (1973) proposed the use of month-by-month cross-section regression of monthly returns on betas instead of estimating a single cross-sectional regression of average monthly returns on betas. This, they said, would address the problem of inference caused by the correlation of residuals in cross-section regression. They remarked that the standard errors of the average intercept and slope fully capture the effects of residual correlation on variation in the regression coefficient, but sidestep the problem of actually estimating the correlations. This is resolved by the standard approach of capturing the residual correlation via repeated sampling of regression coefficients.

The Sharpe-Lintner CAPM also implies a time-series regression test as identified in Jensen (1968).

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \varepsilon_{it}, (2.5)$$

This implies that Jensen's alpha, the intercept term in the time-series regression in 2.5, is zero for each asset. Early tests squarely reject the Shape-Lintner CAPM, citing a positive but flat relation between beta and average return, as stated in Friend and Blume (1970), Black, Jensen and Scholes (1972), and Stambaugh (1982). The intercepts in time-series regressions of excess asset return on the excess market returns are negative for assets with high betas and positive for assets with low betas. However, when average returns are considered, the relation with beta becomes approximately linear. This is consistent with Black CAPM.

2.2.4.2 Market beta and expected return

The CAPM insists on mean-variance-efficiency as reflected in the Sharpe-Lintner and Black versions of the CAPM. This means that other variables add nothing to the explanation of expected return as the sole explanatory variable of expected return is market beta. Along with the tests on risk premiums, other early tests focus on this prediction of differences in market beta as the sole explainer of differences in expected excess return across securities and portfolios, and the method usually employed is cross-sectional regression, although time-series regression can also be employed. Tests on this carried out by Fama and MacBeth (1973) show results that are consistent with the findings in the Sharpe-Lintner and Black CAPM.

Borrowing inferences from Gibbons, Ross and Shanken's (1989) test, a candidate for the tangency portfolio T (in Figure 2.1) is constructed by optimally combining the market proxy and the assets on the left-hand side of the time-series regressions. In effect, this statistic tests whether the market proxy is the tangency portfolio that can be constructed by combining the market portfolio with the specific assets used as dependent variables in the time-series regression. We can see similar interpretations of the cross-section regression test regarding the explanation of expected return by market betas. However, an important inference from this discussion as stated in Fama and French (1994) is that cross-section and time-series regression do not, strictly speaking, test the CAPM; they only test specific proxies of a market portfolio to ascertain if they are efficient in the set of portfolios that can be constructed from it and from assets on the left-hand side that are not explained by the market beta. As stated in Roll (1977), this is because the model does not contain all marketable assets and data for the true market portfolio of all assets are likely beyond reach.

However, it is worth noting that the evidences from both cross-sectional and time-series regression do not disprove the predictions of the Black CAPM as the standard market proxies seem to be on the minimum variance frontier. But the predictions of the Sharpe-

Lintner CAPM regarding the premium per unit of beta being the expected market return minus the risk-free rate of interest is constantly rejected in empirical research.

Most tests of the CAPM are conducted within the developed markets or the Asian emerging market; this study will seek to investigate the premium per unit of beta theorised by the CAPM within the African equity markets.

2.2.5 The three-factor model and other tests of the CAPM

Further evidences against the CAPM have continued with Reinganum (1981), Stambaugh (1982) and Lakonishok and Shapiro (1986) stating that the relationship between beta and average return is even flatter beyond the sample period in the early CAPM. Statistical uncertainty (a large standard error) does, however, cloud the estimates of beta premium. Attempts have also been made to revive the Sharpe-Lintner CAPM by the likes of Kothari et al. (1995), who attribute the weak link between average return and beta to chance. Fama and French (2004) insist that this argument is irrelevant, citing the fact that other variables capture the variations in expected returns that are missed by beta.

Other extensions of the CAPM include those of Merton (1973) and Breeden (1979), which allow for multiple time periods and investment opportunities that change from one period to the next. Solnik (1974), Stulz (1981) and Adler and Dumas (1983) extended the CAPM to international investing and the earlier discussed extension by Ross (1976), who relaxed some of the assumptions by relying on the arbitrage process. Perhaps the most important extensions of the CAPM come from Fama and French (1992, 1996), who added two more risk factors to the traditional CAPM model to form the three-factor CAPM model as:

$$E(R_{it}) - R_{ft} = \beta_{iM}\left[E(R_{Mt}) - R_{ft}\right] + \beta_{is}E(SMB_t) + \beta_{ih}E(HML_t) \quad (2.6)$$

where $E(R_{it}) - R_{ft}$ is the expected return on a portfolio in excess of the risk-free rate, $R_{Mt} - R_{ft}$ is the excess return on a broad market portfolio, SMB_t (small minus big) is the difference between the return on a diversified portfolio of small stocks and that of large stocks while HML_t (high minus low) is the difference in return of a diversified portfolio of high and low book-to-market stocks. $E(R_{Mt}) - R_{ft}$, $E(SMB_t)$ and $E(HML_t)$ are expected premiums and the betas are slopes in the time-series regression,

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \varepsilon_{it}. \quad (2.7)$$

They found that this combination of size and book/market ratio performs best in explaining the cross-sectional variations in stock returns. More interestingly, they found that when these two factors are accounted for, CAPM beta becomes insignificant. Like Fama and French (1992), Basu (1977) found earnings-to-price multiples to be positively significant while Banz (1981) found size (value of equity) to be negatively related to average stock returns. Similarly, Stattman (1980) and Rosenberg et al. (1985) find that on average high book-to-market stocks return more than the CAPM. Others document that the deviations from the linear CAPM risk-return trade-off are related to leverage (Bhandari, 1988) and book-to-market value (Chan et al. (1991)). However, unlike these studies, Fama and French (1992) insist that beta is dead, as they found it insignificant.

A major rebuttal of the findings of Fama and French (1992) comes from the works of Kothari, Shanken and Sloan (1995), who insist that using beta estimates from annual rather than monthly returns produce a stronger positive relation between average return and beta. This is because true beta can vary systematically and non-linearly with the length of the interval used to measure returns; hence inferences from cross-sectional regression of average returns on beta can be sensitive to the return measurement interval used to estimate betas. Also, estimates of beta are biased in the short term, as stated in Scholes and Williams (1977) and Cohen et al. (1983), and this bias results from trading frictions and non-synchronous trading.

Lo and MacKinlay (1990) and Mech (1993) also agree to biased estimates of beta in the short term, but they highlight that this is due to systematic cross-temporal covariances. Lastly, monthly returns appear to have a seasonal component that is quite significant, as stated in Keim (1983), but this seasonal component is not very well understood, as Rozeff and Kinney (1976) note. According to Kothari, Shanken and Sloan (1995), these biases can be mitigated using longer-interval return observations such as using annual returns, but they also admit that in the case of mitigating the complications that arise from seasonality in returns, it may not be the best.

Similar findings were also reported in Ball and Kothari (1989) using size portfolios. This also provided evidence in support of beta in accounting for cross-sectional variations in expected returns. The question of selection bias in the data used by Fama and French (1992) has also been raised in the literature. This suggests that the returns on high book-to-market portfolios formed using the COMPUSTAT data may be spuriously inflated because of missing data and several years of surviving firms' historical data being included in the database. Kothari, Shanken and Sloan (1995) also highlighted data-snooping arising from their claim that variables other than size and book-to-market value were examined and eliminated. As a result, they doubted that the findings of Fama and French (1992) would be robust to longer periods.

Kothari, Shanken and Sloan (1995) do, however, recognise that there are valid economic arguments for ratios such as earnings or dividend yield and book-to-market values to be positively related to expected return beyond beta. These were also confirmed in Sharathchandra and Thompson (1993) and Ball (1978).

With Fama and French (2015) calling into question their very own prediction about the importance of book-to-market value in asset pricing, this study will investigate the Fama/French factor within the market with different characteristics – the African equity market. Thus, it is hypothesised that there is a positive relationship between beta and returns, a positive relationship between size and returns and a positive relationship between book-to-market value and returns.

2.2.6 The four-factor CAPM

One of the most popular of these models is the four-factor model of Carhart (1997), which includes momentum as measured in Jegadeesh and Titman (1993). According to Novy-Marx (2012), momentum trading refers to buying past winners and selling past losers. Evidences have been provided by numerous researchers on the profitability of momentum trading strategies (e.g. Griffin et al., 2003, Jegadeesh and Titman, 1993, 2001, Jagadeesh

1990, Chui et al., 2003, Rouwenhorst, 1998, 1999, De Bondt and Thaler 1985), but there remains to be seen a consensus on the source of these profits. Badrinath and Wahal (2002) highlight the implication of momentum trading for the efficient markets by stating that it destabilises stock prices, which contrasts with Friedman's (1953) argument, which insists that rational speculation must stabilise asset prices. Unlike the findings in Fama and French (1992), Carhart (1997) finds beta to be significant.

However, the profitability of momentum trading strategies has also come under severe scrutiny, with Novy-Marx (2012) insisting that the predictive power of immediate past performance has diminished over time. They also emphasise that doubts still exist on the ability of momentum to predict returns during different time periods and in different markets. However, it is hypothesized in this study that there is a positive relationship between momentum and returns.

2.2.6.1 Measuring momentum

According to Jagadeesh and Titman (1993), momentum trading strategies that buy stocks that have recently performed well and sell stocks that have recently performed poorly can generate significant positive returns. Measurement of momentum largely follows the approach identified in Jegadeesh and Titman (1993), which selects stocks based on their past J month return and hold them for K months. As stated in Gutierrez Jr and Hameed (2007) and Siganos and Chelley-Steeley (2006), overlapping holding portfolios are examined to increase the test strength. Chui, Titman and Wei (2003), Rouwenhorst (1999) and Siganos and Chelley-Steeley (2006) have all documented momentum over 3–12-month horizons in different markets.

However, Fama and French (1996) insist that the momentum anomaly results from data-snooping, while Lesmonda et al. (2004) and Korajczyk and Sadka (2004) admit that the profitability of momentum trading becomes very doubtful in the presence of direct and indirect transaction costs. Conrad and Kaul (1998) and Bulkley and Nawisah (2009) report that momentum profit can virtually all be traced to cross-sectional variation in unconditional mean returns. In their defence, Jegadeesh and Titman (2002) refute these claims and relates the findings of Conrad and Kaul (1998) and Bulkley and Nawisah (2009) entirely to small sample biases in their estimates. Surely, past performance should persist indefinitely if momentum profits were primarily due to cross-sectional difference in mean returns, but Jegadeesh and Titman (2001) insist that momentum trading is only profitable during the first 12 months after portfolio formation and mostly due to time-series dependence in realised return.

2.2.7 Behavioural finance and asset pricing

Other variants of the CAPM include those from the standpoint of behavioural finance and psychology, where proponents argue that the psychology of the investors affects their perception of risk in particular and investment behaviour in general, hence affecting expected returns. For example, reversal in long-term returns documented in De Bondt and Thaler (1985) and Chopra, Lakonishok and Ritter (1992) claim that stocks with low 2–5-year past returns tend to have higher 2–5-year future returns. Others like Shu (2010) insist that mood affects expected returns through affecting investors' rational cognitions, risk assessment and preferences. Research into the effect of mood on investment uses proxy variables such as beliefs (as in Dowling and Lucey, 2005), biorhythms (as in Yuan at al., 2006, and Kamstra et al., 2003) and weather (as in Shu and Hung 2009, Keef and Roush 2007, Chang et al., 2006, Cao and Wei, 2005, and Hirshleifer and Shumway, 2003). They believe that investment returns and asset prices fluctuate with investor mood. Other behavioural factors that affect asset prices include chaos (Clyde and Osler, 1997), disequilibrium (Beja and Goldman, 1980) and noisy rational expectations (Blume, Easley and O'Hara, 1994).

A good starting point is to state some of the objections of behavioural finance to asset pricing and the objections of the fully rational approach.

Table 2.2: Common objectives to the psychological approach to asset pricing and parallel objectives to the full rational approach (Source: Hirshleifer, 2001)

Objections to psychological approach	Objections to fully rational approach
Alleged psychological biases are arbitrary.	Rational in finance theory requires impossible power of calculation.
Experiments that generate alleged psychological biases are not meaningful.	The evidence we possess does not support rational behaviour.
It is easy to go theory fishing for psychological biases to match data ex-post.	It is easy to go theory fishing for factor structure and market imperfections to match data ex-post.
Rational traders arbitrage away mispricing.	Irrational traders should arbitrage away efficient pricing.
Rational investors will make better decisions and get richer.	Irrational investors will bear more risk and get richer.
Confused investors will learn their way to good decisions.	Accurate investors will learn their way to bad decisions.
Apparent return predictability is spurious, so psychological models of predictability are misguided.	Apparent returns predictability is spurious, so rational models of predictability are misguided.

In recent years, there has been a significant increase in literature investigating the impact of behavioural biases on asset prices. These literatures have argued that the central task of asset pricing is to examine how expected returns are related to risk and to investor misvaluation. Several proxies have been used to measure misevaluation, including measures of public mood (such as the weather), actions possibly taken to exploit mispricing (such as insider purchase or recent occurrence of a stock repurchase) or price-containing variables (such as earnings/price, market value, book/market value). Edmans et al (2007) note that the measures of mood largely take the form of either linking returns to single events, as in Frieder and Subrahmanyam (2004) and Kamstra et al (2000), or a continuous variable, as in Yuan et al. (2006) and Hirshleifer and Shumway (2003).

Hirshleifer (2001) moved away from the psychological determinants of rational risk aversion and time preference to focus on the psychology of imperfect rationality. He analysed this using judgement and decision biases, evidence of risk and mispricing effect, and asset-pricing theories based on investor psychology. In analysing judgement and decision biases, he insists that the explanation for these come from emotional loss of control, self-deception and heuristic simplification. The effect of these, other behavioural biases and heuristics on investment decisions are analysed as follows.

2.2.7.1 Overreaction and underreaction

As stated in Andrikopoulos (2007), overreaction and underreaction are the two most important hypotheses that can partially explain the price equilibrium anomalies. Several studies have investigated the initial stock-price reaction to earnings information and find that this initial reaction can be too large or too small. As highlighted in Abarbanell and Bernard (1992), some authors report that stock prices underreact to earnings announcement with a "post-earnings announcement drift" resulting from a subsequent completion of the reaction in stock prices. De Bondt and Thaler (1987 and 1990) find evidence consistent with overreaction to earnings and establish a link in explaining long-term reversals of extreme prior stock-price changes that occur as overreactions correct. This is also supported by De Bondt and Thaler (1985).

The tendency to overreact and deviate from Bayesian, optimum, rational decision-making arises from psychological biases such as *representativeness, anchoring and adjustment, leniency and conservatism heuristics*, as seen in Kahneman and Tversky (1973), Kahneman et al (1982) and Daniel et al (1998). According to Amir and Ganzach (1998), representativeness and anchoring and adjustment influence the extremity of predictions. Representativeness heuristic is the "illusion of seeing the patterns in random walk or more generally in order among chaos", as identified in Andrikopoulos (2007). This leads people to choose a prediction value whose extremity matches the extremity of the predictive information, as seen in Kahneman and Tversky (1973). As seen in Andrikopoulos (2007), a series of company performances that is positive will be taken by investors to represent continuous growth potential, ignoring the possibility that this performance is of a random nature. This leads to excessive optimism and overvaluation of the company's prospects.

The anchoring and adjustment heuristic leads to excess moderation (i.e. underreaction). This heuristic causes investors to anchor at some salient value and adjust based on predictive information. This adjustment is, however, typically insufficient, causing the predictions to be excessively moderate, as also seen in Slovic and Lichtenstein (1971) and Kahneman and Tversky (1973). Leniency, on the other hand, leads to overly optimistic (lenient) predictions. This has been investigated by other authors, including Givoly and Lakonishok (1984). In offering some insight into this heuristic, De Bondt and Thaler (1990) and Affleck-Graves et al. (1990) identify the possibility that analysts have a preference to maintain good relations with management. Amir and Ganzach (1998) identify that this preference for maintaining good relations with management causes analysts to offer optimistic forecasts that may be stronger in the presence of unfavourable stock recommendations. This was supported by the research in Francis and Philbrick (1993).

The conservatism heuristic, as stated in Edwards (1968), relates to the conditions where an investor is subconsciously reluctant to alter their beliefs in the face of new information. This heuristic impacts investment decision-making through the fact that even if investors' beliefs change as a result of the availability of new information, the magnitude of the change will be relatively low when compared to change under rational conditions. The importance in the overreaction and underreaction hypothesis is that investors will only partially evaluate new information or even disregard it altogether, if it is not in line with their beliefs. According to Andrikopoulos (2007), beside the conservatism psychological state, the heterogeneity of the investing public can cause investors' underreaction to new information. This arises from the fact that investors do not have equal access to information, hence information diffuses slowly to investors.

Abarbanell and Bernard (1992) highlight the anomaly in stock-price behaviour around earnings announcements, which may be rooted in a failure by market participants to appreciate what the current earnings imply about future earnings. Brennan (1991) indicates that stock prices appear to reflect expectations of quarterly earnings that are anchored too heavily on the earnings of the corresponding quarter of the prior year, hence underreacting to current news. In contrast to underreaction to earnings, De Bondt and Thaler (1987) explain how investor "myopia" could result in an overemphasis on earnings from the recent past. De Bondt and Thaler (1987) support the assertions with evidence consistent with generalised overreaction. They highlight the extreme difference between forecast earnings changes and actual changes estimated by analysts and conclude that analyst estimates are just too extreme to be rational.

Another phenomenon that has a significant impact on the overreaction heuristic is the impact of analysts' coverage on some stocks. As identified in Andrikopoulos (2007), small stocks that have no coverage exhibit a strong overreaction effect as they are usually excluded from analysts' coverage and recommendations. Hong and Stein (1998) identify that when these small stocks have low analysts' coverage, information flows gradually, causing these stocks to exhibit the strongest reversal effect. Along with information flow and judgement bias, the behaviour of investors also contributes in explaining underreaction and overreaction as identified in Andrikopoulos (2007).

2.2.7.2 Overconfidence

According to Scott, Stumpp and Xu (2003), the overconfidence hypothesis suggests a systematic mispricing of public information by investors. This hypothesis identifies that investors are overconfident about their ability to predict the future. This is also supported by De Bondt and Thaler (1995), who identify overconfidence as a pervasive human characteristic. Andrikopoulos (2007) identifies that investors arguably fail to correctly define the length of the short and long run. This was supported by Jegadeesh and Titman (1993) and Haugen (1995); this along with biased self-attribution leads to excessive optimism about certain stocks, while simultaneously reducing the chance or probability of correcting their beliefs.

Self-attribution relates to the fact that individuals tend to strongly attribute events that confirm the validity of their actions to high ability, while at the same time attributing events that do not confirm their actions to external reasons. According to Andrikopoulos (2007), these elements reinforce behavioural finance's overconfidence hypothesis, where investors' erroneous memory indirectly eliminates consideration of the correct alternative outcomes. A detailed overview of overconfidence is found in Odean (1998), where overconfidence is found to exist in many professional fields, not just in finance. However, Odean (1998) insists that participants in the financial markets are more overconfident than the general population due to selection bias. Self-enhancing bias also causes overconfidence in wealthy traders who are not in danger of being driven out of the marketplace, as highlighted in Gervais and Odean (2001). Odean (1998) asserts that it is not overconfidence that makes them wealthy, but the process of becoming wealthy contributes to their overconfidence.

In concluding, Odean (1998) finds that "overconfidence is costly to the society". Overconfident traders have the tendency not to share risk optimally; they expend too many resources on the acquisition of information and trade too much. He also identified that overconfidence increases trading volume and market depth, but decreases the expected utility of overconfident traders. Daniel, Hirshleifer and Subrahmanyam (1998) identify an asset-pricing model that incorporates a version of the overconfidence hypothesis. Others who find evidence consistent with overconfidence include Daniel and Titman (1999).

2.2.7.3 Mean-reversion hypothesis

According to De Bondt and Thaler (1989), one of the most popular finance concepts relates to the "efficiency" of the market and the fact that security prices in efficient markets reflect their intrinsic value. Brealey and Myers (1988) highlight that efficient capital markets "have no memory"; this relates to assertion that future prices are unpredictable. However, in a world made up of noise traders, there can be no certainty that rational traders dominate the market such that noise traders become extinct. De Bondt and Thaler (1989) highlight that indeed under possible conditions rational arbitrageurs can even be outperformed by noise traders. They also indicate that prices do not always equal intrinsic value.

However, since prices tend to move towards fundamentals, over the long run, they will be mean-reverting. This indicates that they are not a random walk and indeed predictable. This is similar to the question posed by Fama (1965) regarding whether stock prices are predictable or not; he concludes that "it is safe to say that the evidence is in favour of the random walk theory".

However, in his later paper with French (Fama and French, 1989), they admit that the evidence is in support of predictability of prices. This was also supported by Lewellen (2001). Lewellen and Shanken (2002) assert that in an efficient market, investors should be aware of any cross-sectional or time variation in expected return; hence predictability simply reflects changes in the risk premium. This implies that researchers must judge if predictability is consistent with rational behaviour or whether it is better explained by irrational mispricing.

Poterba and Summers (1988), Lo and MacKinlay (1988), and Clark (1987) challenge the conventional view and find evidence that stock returns are characterised by positive autocorrelation over intervals under a year and by negative autocorrelation over longer intervals. The long-run negative autocorrelation does, however, indicate some evidence of mean-reversion behaviour in stock prices. These studies employed Cochrane's (1988) variance-ratio methodology.

2.2.7.4 Ambiguity aversion

According to Stracca (2004), an ambiguous situation is a situation where the probability distribution is unknown. This, he says, is disliked by agents' even more than a risky situation, which he defines as a situation where the probability distribution is known. A good review of ambiguity aversion literature is provided in Camerer and Weber (1992). To handle these "ambiguous" situations, Savage (1954) developed the subjective expected utility, where expectations of a utility function can represent preferences under certain axioms and is time-weighted by the individual's subjective probability assessment. In Ellsberg's (1961) experimental work, otherwise known as Ellsberg paradoxes, people dislike occasions where the probability distribution of a gamble is uncertain, thus causing irrational choices. As expressed in Heath and Tversky (1991), agents feel a particularly strong distaste for ambiguity when there is a perception of limited information. They also insist that an agent's feeling of incompetence in assessing a relevant distribution also results in ambiguity aversion.

Peters and Solvic (1996) support this view, but observe that ambiguity aversion seems to reflect a more general tendency for emotions such as fear to affect risky choices. Barberis and Thaler (2003) provide more examples of various contexts where ambiguity aversion may appear. According to Hirshleifer (2001), because of the uncertainty of outcomes and the structure of economic surroundings, risk premiums of newly introduced financial markets may increase unduly due to ambiguity aversion. This results from the obvious absence of an identifiable parameter of the decision problem, which most times are associated with hostile manipulation and higher risk.

2.2.7.5 Mood, feeling and decisions

Most researchers believe that mood and emotions affect people's perception of risk, thus affecting their judgement and decision-making, and hence altering investing behaviour. As a result, asset prices and returns fluctuate with investor mood. The research on the effect of mood on decision-making includes those on the association between good mood and fast and efficient decision-making (Forgas, 1998), and those on its role as a focusing mechanism in economic decision-making (Etzioni, 1998). Others believe that mood has an influence on the integration of information (Estrada et al., 1997), cognitive process (Isen, 2001) and in preference (Loewenstein, 1996; Mehra and Sah, 2002).

Loewenstein et al. (2001) show that emotions can affect, and sometimes override, rational cognitions when the decisions involve risk and uncertainty. Other sources investigate the effect of mood on perception, with misattribution being the most quoted. According to Schwarz and Clore (1983) and Frijda (1988), misattribution occurs when people attribute their feelings to the wrong sources, thus causing incorrect judgement. Nofsinger (2005) remarked that mood can be the difference between an investment in assets with various degrees of risk, as he admits that people in a good mood are more likely to invest in risky assets than those in a bad mood. Forgas and Ciarrochi (2001) point out that a good mood sometimes makes people assign higher values to both potential and actual wealth, while Wright and Bower (1992) insist that people in a good mood tend to be more optimistic than those in a bad mood with regards to their judgement.

Using the sale of lottery tickets after a football victory by the Ohio State University, Arkes, Herren and Isen (1988) reveal that sports results affect people's optimism or pessimism about not just their own abilities, but life in general. Bizman and Yinon (2002) and Platow et al. (1999) admit that this may also affect investors' view of future stock prices. However, Shu (2010) confirms that the complexity of a decision and the environment also has an influence on the effect of mood on judgement and decision-making. Simplified rules or heuristics seem to be the basis of decisions when there is partial or incomplete information; thus as MacGregor et al. (2000) state, it is much easier to use an affective impression in decision-making than judging probabilities when the decision is full of uncertainty or can be perceived as complex. These studies show that changes in investors' emotional state can affect market prices even when the cost-benefit effect of the underlying event is economically neutral. As Hanoch (2002) and Kaufman (1999) explain, under bounded rationality people rely on their emotions to make satisfying decisions.

Shu (2010) insists that the effects of mood also depend on mood status, not just on decision characteristics, suggesting that emotional factors affect people in a good mood easily. Schwarz and Bless (1991) add that optimistic judgement is typically connected to good mood and tends to cause heuristic styles of information processing. This follows from Schwarz's (1990) mood-as-information theory, which states that "people tend to make decisions that are congruent with their moods". Furthermore, he reports that people in a bad mood tend to react strongly to relevant news, unlike people in a good mood who are prone to react to irrelevant news. Hence, unlike people in a good mood, those in a bad mood are less optimistic about the future. Those in a good mood rely more on heuristic styles of information processing and are more willing to invest in risky assets. This is in line with the findings in Nofsinger (2005).

In terms of evidences, a wide array of financial studies have attempted to link stock prices to investor mood. Parrott and Sabini (1990) and Schwarz and Clore (1983) both documented relationships between weather, mood and stock prices, while Shu (2010), Pilcher et al. (2002), Anderson (2001), Rotton and Cohn (2000) and Schneider et al. (1980) document the influence of weather on behaviour.

Geomagnetic storms, wind, temperature and sunshine are some of the weather variables that are known to correlate with stock prices. These all point to the conclusion that mood misattribution, which guides investors to optimally priced stocks, is triggered by a good mood, brought about by pleasant weather. Negative correlations between geomantic storms and stock returns were found by Krivelyova and Robotti (2003). Thus, stock prices rise only on days of quiet geomagnetic activity, but fall following high geomagnetic activity. They disclose that this arises because investors misattribute their bad mood resulting from geomagnetic storms to negative economic conditions, which tends to make them sell stock on days with geomagnetic storms. In the same vein, wind, as reported in Shu and Hung (2009) and Keef and Roush (2007), and temperature, as in Keef and Roush (2007) and Chang et al. (2006), affect stock prices.

Also, Hirshleifer and Shumway (2003) and Saunders (1993) report a relationship between sunshine and stock returns. They insist that investors are more likely to buy stock on sunny days due to their optimistic mood. This is in line with other research in the realm of psychology that suggests that an increase in sunshine hours leads to a decrease in scepticism and depression (Howarth and Hoffman, 1984, and Eagles, 1994) and an increase in optimism and general good mood (Persinger, 1975, and Howarth and Hoffman, 1984). Following on from weather effects, long winter nights induce depression, which makes investors more risk-averse. Kamstra et al. (2003) attribute this to seasonal variation in stock returns, which is explained by seasonal affective disorder (SAD). Using new moon and full moon, Yuan at al. (2006) argue that stock returns are significantly lower on the days around a full moon than on the days around a new moon. These, they say, result from the tendency for investors to value stocks lower due to the depressed mood associated with a full moon.

According to Shu (2010), the strength of the mood effects depends largely on the complexity of the decision. Also, its effect on the stock markets depends on investor mood status with Dowling and Lucey (2005) insisting that a positive, recent market performance enhances the relationship between mood and equity returns.

2.2.7.6 Self-deception

According to Hirshleifer (2001), "self-deception theory implies overconfidence". In cognitive psychology, as stated in Odean (1998), people are usually overconfident and value the accuracy of their knowledge more than it truly is. This is supported by Lichtenstein et al (1982), Keren (1991) and McClelland and Bolger (1994). This is in line with the fact that people weigh different types of information differently, underweighting some and overweighting some. Kumar (2009) adds to this by stating that investors sometimes overestimate either the quality of the information they possess or their ability to process it due to overconfidence. Hirshleifer (2001) supports this view and admits that their predictions of probabilities are often too extreme, too low relative to the true frequency when they think the event will probably not occur and too high when they think it will.

Attitudinal changes resulting from actions can explain self-deception. Harmon-Jones and Mills (1999) identify that these are the same attitudinal changes that motivate the theory of cognitive dissonance. Hindsight bias is another factor that can lead to self-deception, where individuals feel that they "knew it all along", which helps their self-esteem. To maintain this self-esteem, individuals also interpret ambiguous evidence to rhyme with prior beliefs; this is referred to as confirmatory bias in Gilvoich (1991). Another individual bias that affects asset pricing, as detailed in Hirshleifer (2001), includes heuristic simplification. These include attention, memory, ease-of-processing effects, narrow framing, mental accounting, reference effects and the representativeness heuristic, belief updating (combining effects).

Other evidences provided in Hirshleifer (2001) include evidence of risk and mispricing effects such as predictability of security returns, predictability based upon factor risk measures, predictability based upon price and benchmark volume measures, predictability based upon past returns, momentum and reversals, predictability based upon public versus private news events and predictability based upon mood proxies. They also examine positive feedback trading, pure noise trading, mistaken beliefs, alternative preferences and evolving population.

2.3 CAPM in developed versus developing economies

The Sharpe-Lintner CAPM and other variants are presumed to hold a diversified portfolio of equities in a world market portfolio. As identified in Harvey (1995a), the portfolio risk then becomes the variance of this well-diversified portfolio. The covariance of an individual security with this world portfolio then becomes the risk of that individual security and, usually, beta results from scaling these covariances by the variance of the world portfolio. As identified in Harvey (1991), most tests of this mean-variance efficiency of the world market have failed to reject the CAPM. However, most of these tests were carried out in developed markets and only a few in developing markets.

In analysing the distribution characteristics of emerging market returns, Bekaert et al. (1998) found that emerging equity markets have high volatility, low correlation with developed markets and within the emerging markets, high long-horizontal returns and predictability above and beyond what is found in developed market returns. They also indicate that the efficient frontier is pushed forward when emerging market returns are plugged into the standard Markowitz (1959) framework. This is because of a combination of low correlation and high expected return. They conclude that because emerging market returns cannot be completely characterised by the traditional mean-variance measures of the CAPM, application in these markets becomes problematic. Beyond the expected return, variance and covariance measures, returns in emerging markets show significant skewness and kurtosis.

Investors in these markets will need to keep tabs on asset skewness and coskewness as investors have a preference for positively skewed distributions, as documented in Hwang and Satchell (1999) and Harvey and Siddiqui (1999, 2000). Bekaert et al. (1998) identify further complication in the presence of skewness and kurtosis in emerging markets; they highlight that skewness and kurtosis change through time. This suggests that over time there could be major changes in the returns characteristics. This drastic change usually happens as the market moves from a state of segmentation to a state of integration, which can lead to structural breaks. This evolution causes changes in the fundamental sources of risk from the local economy to the world economy.

Harvey (1995) points out that because investors require compensation for bearing local, idiosyncratic risk, the cost of capital in segmented markets will be higher than in integrated markets. This means that an increase in financial integration should lead to decreases in cost of equity. In a more formal way, Stulz (1999) shows that in a CAPM framework, internationally integrated markets will have a risk premium that depends on covariance between the markets and the world market portfolio. The market should experience a decline in the cost of capital as it becomes internationally integrated, provided that the market’s variance of return is greater than its covariance with the market.

2.4 Liquidity risk and asset pricing

CAPM does face a couple of additional problems in emerging markets apart from those created when its assumptions are relaxed. Collins and Abrahamson (2006) emphasise that these additional problems relate to the use of beta as a measure of risk. Using a sample of 20 emerging markets, Harvey (1995a) found that between 1979 and 1992 betas significantly different from zero were found in only seven emerging markets, with a beta greater than 1 found in only one market. This means that compared to developed markets, the required returns in these emerging markets are very low as they hold very low risk.

This is different from findings in developed markets where all betas are significantly different from zero and generate acceptable required returns. Beta does not accurately measure the risk in emerging markets as it fails to explain any cross-sectional variation in expected returns in a single-factor model framework. According to Hearn and Piesse (2009), this poor performance of the single-factor CAPM model highlights the importance of including a measure of liquidity in the pricing model. They go on to explain that significant bias in the beta is added through low variances and covariance between series, created through a high degree of price rigidity resulting from the presence of severe illiquidity problems in these markets. Liquidity is an elusive and broad concept, as stated in Pástor and Stambaugh (2003). It generally denotes the ability to trade large quantities of stock quickly, at a low price and without moving the market.

Correia and Uliana (2004) and Martinez et al. (2005) point out that the one-factor CAPM fails to account for the well-documented effects of size and liquidity in explaining variation in returns. Mishra and O'Brien (2005) found similar results but using a two-factor model that accounts for market risk and political risk, which relates variations in individual stocks to variations in the market portfolio. However, Lesmond (2005) raised some concern on the omission of liquidity risk, which also explains political risk and the assumption that emerging markets are integrated with the global market portfolio. The importance of liquidity has also been emphasised by Pástor and Stambaugh (2003), who suggest that liquidity is an important variable in asset pricing. They find that stocks with higher sensitivity to aggregate liquidity generate higher return than low-sensitivity stocks.

Acharya and Pederson (2005) present three forms of liquidity risk: the covariance of a stock's liquidity with the market liquidity, return sensitivity to market liquidity, and liquidity sensitivity to market returns. These three forms of liquidity risk and the standard market beta make up the "net beta". Within their liquidity-adjusted CAPM, they find a positive relationship between the expected return on a security and both its expected illiquidity and net beta. The net beta is proportional to the covariance of its expected return, net of its exogenous illiquidity costs, with the market portfolio's net return.

Using the theory of stochastic discount factor, Wang and Chen (2012) developed a liquidity-adjusted, conditional, two-moment CAPM and a liquidity-adjusted, three-moment CAPM models. They found that using the liquidity-adjusted, two-moment model, a security's conditional expected return consists of the liquidity risk premium, the systematic risk premium and its conditional expected liquidity cost. On the other hand, using the liquidity-adjusted, three-moment model, they found that a security's conditional expected return depends on its conditional expected liquidity cost, the conditional covariance between its return and the market return, the conditional covariance between its liquidity cost and the market liquidity costs, and the conditional coskewness of its return and the market return.

Liquidity has also been found to be significant in developed markets, as revealed in Pástor and Stambaugh (2003). They found between 1966 and 1999 that stocks with higher liquidity betas had higher returns within the US market, with an abnormal alpha of 7.5% for a model that also accounts for market, size, value and momentum factors. Other studies that investigated liquidity in developed markets include Datar, Naik and Radcliffe (1998) and Fiori (2000), who all found that less liquid stocks have higher expected returns. Chordia et al. (2001), using volume and turnover data, found a significant cross-sectional relation between stock return and variability of liquidity. They concluded that stocks with more volatile liquidity have a lower expected return.

Daniel and Titman (1997) and Liu (2006) insist that the one-factor CAPM and even the three-factor CAPM of Fama and French (1992) do not capture cross-sectional stock returns. Martinez et al. (2005) find similar results but observe that the size variable does have some explanatory power. With particular reference to emerging markets, Jun et al. (2005) finds a positive relationship between stock returns and liquidity. Hearn and Piesse

(2009) conclude that liquidity and size are significant in explaining cross-sectional returns, while rebuffing the usefulness of book-to-market values in emerging markets due to limitations in obtaining consistent accounting book values.

The liquidity measure employed by Hearn and Piesse (2009) uses the bid-ask spread and commission costs and is specified as:

$$Quoted\ spread_M = \frac{1}{2}\left[\left(\frac{(Ask_M - Bid_M)}{(Ask_{\ M} + Bid_M)/2}\right) + \left(\frac{(Ask_{M-1} - Bid_{M-1})}{(Ask_{M-1} + Bid_{M-1})/2}\right)\right] \quad (2.8)$$

Bid-ask spreads that exceed 80% are trimmed as these are potentially errors, as stated in Lesmond (2005).

Another measure of liquidity is the turnover-adjusted measure in Liu (2006), where the liquidity measure of a security, LM_x, is defined as the standardised turnover-adjusted number of zero daily trading volume over the prior x months ($x = 1$, 6, 12), represented as:

$$LM_x = \left[(Number\ of\ zero\ daily\ volumes\ in\ prior\ \times months) + \frac{\frac{1}{x} month\ turnover}{Deflector}\right] \times \frac{21x}{NoTD} \quad (2.9)$$

where x month turnover is the turnover over the prior x months. $NoTD$ is the total number of trading days over the prior x months and deflector is chosen such that

$$0 < \frac{{}^{1}\!/_{(x\ month\ turnover)}}{Deflactor} < 1 \quad (2.10)$$

for all stocks. Due to variations in trading days, typically from 15 to 23 days per month, 21x/NoTD standardises the number of monthly trading days to 21, making the liquidity measure comparable over time. $LM1$ is the turnover-adjusted number of zero daily trading volume over the prior 21 trading days, with 1 reflecting the period of measurement.

The assumption made by Hearn and Piesse (2009) is worth noting. The study assumes that the African markets within its analyses are fully integrated, although it does admit that in reality these markets are highly segmented. They also recognise that this problem of integration compounds the problems of choosing a suitable market variable, due to the lack of an appropriate regional benchmark in Sub-Saharan Africa. The model employed by Hearn and Piesse (2009) is Fama and French's (1992) three-factor CAPM, as stated in Equation 2.6, with the HML variable representing the difference between the return on a portfolio of high illiquidity stock and of low illiquidity stocks. Equation 2.6 is also transformed in Equation 2.7 in order to test the model with historical data. They find that size and liquidity factors considerably improve the explanation of cross-sectional stock return. Hence it is hypothesised that liquidity is directly related to returns.

2.5 Effects of market segmentation on estimates of the CAPM

One of the assumptions of the CAPM is that under equilibrium conditions, expected returns represent fair compensation for a degree of risk each security contributes to the broad market portfolio. However, according to Bruner et al. (2008), the choice between a global index and a home country index as the market portfolio for the regression depends on the level of global market integration. Segmentation is said to exist when investment and consumption opportunities differ between residents and non-residents, leading Stulz (1994) to describe segmentation as a function of investment barriers. Within emerging markets, substantial difference can be made in the estimates of the CAPM when choices are made between global and local market indices, as Mishra and O'Brien (2005) and Bruner et al. (2008) identified. However, emerging markets have become increasingly less segmented, as noted in De Jong and De Roon (2004), and this has led to decreases in the cost of capital of these markets.

When integration is achieved, Koedijk and Dijk (2004) point out that the sensitivity of a stock return to its home country index also captures the stock's sensitivity to global risk factors. Koedijk et al. (2002) and Harris et al. (2003) support these assertions and state that in comparison with the model risk intrinsic to the CAPM, market portfolio is inconsequential. Most researchers on segmentation and liberalisation view liberalisation as a snapshot event where markets are assumed to be completely segmented before a particular liberalisation date and become perfectly integrated afterwards, as stated in Bekaert and Harvey (1995, 2000) and Henry (2000).

These studies focus on official liberalisation dates and/or estimated structural breaks on economic and financial indicators to examine the pre- and post-liberalisation effect on stock markets and the real economy. However, Stulz (1999) insists that integration occurs over time and is usually gradual. Panchenko and Wu (2009) also observe that the process of integration may experience short-term reversals. De Jong and De Roon (2004) insist on the importance of time variation in the level of market segmentation in identifying the effect of liberalisation on estimates of the CAPM.

The importance of time variation in integration follows naturally from an international capital asset-pricing model (ICAPM) with investment restrictions. In the standard international CAPM of Adler and Dumas (1983), markets are assumed to be completely integrated; all investors can freely invest in all countries as there are no investment barriers between countries. As stated in Panchenko and Wu (2009), the ICAPM estimates return-based measures of market integration with implicit assumptions on what kind of risks are priced into emerging markets.

In a segmented state, the variance of a market's return dominates, as theorised in Bekaert and Harvey (1995), while in an integrated state the covariance with world market returns becomes relevant. Panchenko and Wu (2009) indicate that emerging markets will transition between the two. This transition, which is expected to occur over time, indicates that expected return should be time-varying during this period of transition; thus, in reality many emerging markets are partially segmented. To measure market segmentation in a CAPM-type model, De Jong and De Roon (2004) used a ratio of non-investable market value to total market value. This segmentation risk premium will be priced into the expected return of emerging stock markets, which will allow estimates of the effect of market segmentation on expected returns to be made from a simple regression model.

2.6 Contagion

Despite the widespread use of the term contagion, there is neither a universally accepted definition, nor a universally accepted method for testing contagion effect. As stated in Caporale et al. (2005), there is still no consensus on the definition of contagion. In an attempt to unite the definitions/approaches of contagion, the World Bank[14] (2013) proposed classification of the definition of contagion with the following key areas: broad definition, restrictive definition and very restrictive definition.

In the broad definition, it identifies contagion as "the cross-country transmission of shocks or the general cross-country spillover effect". In the restrictive context, it defines contagion as the "transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred to as excess co-movement, commonly explained by herding behaviour". In the very restrictive definition, it remarks that "contagion occurs when cross-country correlation increases during 'crisis times' relative to correlation during 'tranquil times'." For other definitions of contagion, see the excellent summary in Ahmadu-Bello (2014).[15]

Within this study, our concern is mainly on the causes of contagion and the impact of financial integration. One aspect of the cause of contagion relates to fundamental causes that led Bekaert, Harvey and Ng (2005) to remark that contagion relates to the excess correlation above what would be expected from economic fundamentals. In the "wake-up call" theory of contagion, from Ahnert and Bertsch (2014), investors' reassessment of fundamentals in itself can lead to an increased probability of a crisis spreading to other regions. This is supported by Forbes (2012). The fundamentalist view of contagion believes that contagion results from common shocks, trade and financial linkages. See Claessens and Forbs (2004), Hermandez and Valdes (2001) and Patev and Kanaryan (2003).

Away from the fundamentalist view, other authors believe that investor behaviour is the prime cause of contagion, where investors in other countries ignore the differences in

[14] For details on the World Bank classification and definition of contagion, see http://go.worldbank.org/JIBDRK3YC0.
[15] Thesis titled "The 2007-09 Global Financial Crisis and Financial Contagion Effects in African Stock Markets", submitted to Coventry University, UK.

fundamentals among countries. As stated in Dornbusch and Claessens (2000), this is linked to herding behaviour. Other investor behaviours that may lead to contagion are highlighted in Račickas and Vasiliauskaitė (2011). These include liquidity problems, incentive problems, information asymmetry, market coordination problems and investor reassessment.

As identified in Section 2.5, integration has an impact on estimates of the CAPM as sensitivity of a stock return to its home country index also captures the stock's sensitivity to global risk factors when the market is integrated with world markets. In analysing the degree of integration of African markets, Berger, Puthuanthong and Yang (2011) found little evidence of integration in Nigeria, Mauritius and Kenya, but found some level of positive integration in Tunisia, Ghana and Botswana. Agyei-Ampomah (2001) and Boamah (2014) found that South Africa remains the most integrated of the African market, with most other African countries being largely segmented, despite the structural improvements and growth of African stock markets.

If most African markets are segmented, we expect little or no financial contagion resulting from the financial crisis, apart from the South African market; and some political contagion resulting from the Arab Spring, as some of the north African countries were affected. Thus, it is hypothesised that contagion in absent in the African market.

2.7 CAPM under structural breaks

The unconditional CAPM of Sharpe (1964) and Lintner (1965) implies a linear equilibrium relationship between return and risk, with other authors such as Jensen and Scholes (1972) and Fama and MacBeth (1973) confirming this relationship. However, more recent articles, such as those of Fama and French (1992) and Jegadeesh and Titman (1993), find weak or no statistical evidence to support this relationship. Fama and French (1992) explain this lack of statistical evidence by showing that beta is not a complete measure of risk, as they reveal that some fundamental variables such as the size and book-to-market ratio of a portfolio can explain the variations in returns. An alternative explanation comes from evidences supporting significant time variation in market betas despite the linear relationship that guides the Sharpe (1964) and Lintner (1965) CAPM.

Studies supporting the time-varying nature of the relationship between estimated betas and market risk premium include Fabozzi and Francis (1978), Ferson and Harvey (1991, 1993) and Ghysels (1998).

The arguments supporting time variation on market betas has led Jagannathan and Wang (1996) to advocate for a time-varying conditional CAPM to replace the static CAPM. This, however, results in an overstatement of the time variation as it fails to capture the dynamics of beta risk, Ghysels (1998) finds. Thus, Akdeniz et al. (2003) note that it is crucial to understand the dynamics of time variation in betas and include these dynamics in the CAPM. They introduced a new threshold CAPM where beta risk changes through time within the economic environment and also across industries. They confirm that this threshold CAPM outperforms both the conditional and unconditional CAPM models by generating smaller pricing errors.

Huang and Cheng (2003) recommend that the unconditional CAPM can also be used with specifications made to allow for time variation in betas. Other findings in Huang (2000, 2001, 2003) support non-consistency of the betas and also indicate that beta may be stable within one regime and unstable within another regime.

Following from the discussion above, Garcia and Ghysels (1998) argue that the assumption of a constant (stable) relationship between the returns and beta can be seriously questioned due to the presence of structural changes resulting from market liberalisation. They also identified that structural breaks can also be present because of the introduction of new institutions and also as a result of drastic political or economic policy changes. This will mean that we need not always reject or accept the CAPM for the whole period as the single possible result, as the structural change modelling strategy allows for different dynamic behaviour among different regimes, leading to structural changes.

Considerable empirical and theoretical research has been conducted on structural changes, especially for a single change as reported in Bai, Lumsdaine and Stock (1998), Hall and Sen (1999) and Bekaert, Harvey and Lumsdaine (2002). On the contrary, Bai and Perron (2003) focus on multiple changes in a linear model. Their work follows from Bai and Perron (1998), who estimated multiple structural changes in a linear model by least squares. They derived the rate of convergence and the limiting distributions of the estimated break points using a framework of partial structural changes, which allows a subset of the parameters not to change.

Another important development within their work is the use of a sup-Wald-type test for multiple structural breaks. The sup-Wald-type test tests for the null hypothesis of no change versus a pre-specified number of changes and also versus an alternative containing an arbitrary number of changes. They also consider a procedure that allows one to test the null hypothesis of, say, l changes versus an alternative hypothesis of $l + 1$ changes.

Bai and Perron (2003) document that a useful strategy is to carry out the *WD* max or *UD* max test to investigate the presence of at least one break. If a break exists following these tests, a sequential examination of the sup$F(l + 1 \mid l)$ statistics constructed using global minimisers for the break dates can be used to decide the number of breaks. This study will however, hypothesise that there is no structural break in the African market indexes examined.

2.8 Conditional asset-pricing models

The presence of structural breaks suggests that beta may not be constant over time, which is contrary to the assumption of the static CAPM of Sharpe (1964) and Lintner (1965). Jagannathan and Wang (1996) highlight that this assumption is not reasonable as the relative risk of an asset is likely to vary over time. They insist that betas and expected return will, in general, depend on the nature of the information available at any given point in time and vary over time. Some of the points that present a problem to the static (unconditional) CAPM include the rise in the beta of equities during a recession caused by leverage, the varying effect of the business cycle on different types of assets, effects of technological changes and changes in consumer taste.

Looking back at the Sharpe-Lintner-Black (static) CAPM, the model implies a time-series regression test as identified in Jensen (1968) as;

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \varepsilon_{it}, \text{(2.11)}$$

where β is defined as

$$\beta_i = Cov\ (R_{it}, R_{Mt})/Var(R_{Mt})\ \text{(2.12)}$$

Based on cross-sectional returns, the CAPM can be written as

$$E[R_{it} - R_{ft}] = \gamma_0 + \gamma_1 \beta_i \quad (2.13)$$

There is a linear constant relationship between $E[R_{it} - R_{ft}]$ and β_i.

As identified above, this version of the CAPM is the static CAPM as β_i is constant. This version is also referred to as unconditional CAPM, since conditional information plays no role in determining excess returns. However, as documented in Keim and Stambaugh (1986), Breen et al (1989) and Chen (1991), conditional information does play a role in determining excess returns, hence beta may not be constant. For each asset i and in each period t,

$$E(R_{it}|I_{t-1}) = \gamma_{0t-1} + \gamma_{1t-1}\beta_{it-1}, \quad (2.14)$$

where the conditional beta $\beta_{it-1}$is defined as

$$\beta_{it-1} = Cov\,(R_{it}\,, R_{Mt}|I_{t-1})/Var(R_{Mt}|I_{t-1}) \quad (2.15)$$

γ_{0t-1} and γ_{1t-1} are the conditional expected return on a zero-beta portfolio and the conditional market premium respectively. The unconditional expectation of Equation 2.14 will give

$$E(R_{it}) = E(\gamma_{0t-1}) + E(\gamma_{1t-1})E(\beta_{it-1}) + Cov(\gamma_{1t-1}, \beta_{it-1}) \quad (2.16)$$

If $Cov(\gamma_{1t-1}, \beta_{it-1}) = 0$, i.e., a linear function of the expected beta, we have a static CAPM for asset i, hence expected return is a linear function of the expected beta. Generally, $Cov(\gamma_{1t-1}, \beta_{it-1}) \neq 0$. During periods of bad economic conditions, for example, the expected market risk premium is relatively high, more leveraged firms are likely to face more financial difficulties and have higher conditional betas. $Cov(\gamma_{1t-1}, \beta_{it-1}) = 0$ is testable given I_{t-1}, and this forms the base for tests of conditional CAPM.

In analysing the conditional CAPM versus the unconditional CAPM, Lewellen and Nagel (2006) chronicle the findings in Jensen (1968), Dybvig and Ross (1958) and Jagannathan and Wang (1996), who reveal that conditional CAPM could hold perfectly, period by period, even though stocks are mispriced by the unconditional CAPM. They go on to state that if beta is correlated with the equity premium or with market volatility and changes through time, the conditional alpha (pricing error) of the stock might be zero when its unconditional alpha is not. These assertions are supported by the works of Hensen and Richard (1987). Following these studies, other authors argue that the size and book-to-market (B/M) effect identified in Fama and French (1992) can, in fact, be explained by time-varying betas. These authors include Zhang (2005), who showed that high B/M stocks have an unconditional value premium during recessions, when risk premium is high. Lettau and Ludvigson (2001), Lustig and Van Nieuwerberburgh (2005) and Santos and Veronesi (2006) examine the beta of small, high B/M stock over the business cycle and they found that their beta does vary with the business cycle. They also found that these variations do explain the positive unconditional alpha found for these stocks.

However, Lewellen and Nagel (2006) question whether asset-pricing anomalies can really be explained by conditional CAPM. This results from their assertion that conditional CAPM does not explain the B/M and momentum anomalies. They also argue that if the conditional CAPM holds, a stock's unconditional alpha will depend primarily on the covariance between its beta and the market risk premium, and they find the implied alpha to be quite small. However, the empirical evidence provided by Lewellen and Nagel (2006) suggests that the pricing errors observed are just too large to be examined by time variation in beta.

In analysing beta in an international CAPM (ICAPM), Mark (1988) and Ng (1991) find significant time variation in beta. Using an E-GARCH framework, Braun, Nelson and Sunier (1995) find beta not to be time-variant, where beta responds asymmetrically to positive versus negative domestic news or world news. However, using a state-dependent beta in a SWARCH model, Ramchand and Samuel (1998) found strong evidence of state-dependent beta in the Pacific and North America, but in the European markets the evidence found was not significant. In studying a conditional version of the ICAPM for emerging markets, Bekaert and Harvey (1995) conditioned beta on an unobserved state variable taking the value of one or zero.

$$R_{i,t} = \alpha + \beta_1(1 - S_t)R_{m,t-1} + \beta_2 S_t R_{w,t-1} + \varepsilon_{w,t} \qquad (2.17)$$

The unobservable state variable is represented as S_t which Bekaert and Harvey (1995) link to the degree of integration between the emerging market and the world market. They find time variation evidence on β_1 and β_2, consistent with partial integration. It is worth noting that these ICAPM articles focus on time series and do not use exogenous observable information.

Ferson and Harvey (1993), on the other hand, explain cross-sectional expected returns across world stock markets, where they allowed beta to vary over time with local market information variables. But when the market is integrated, they allow the risk premiums to depend only on global information variables. They found several variables (global and asset-specific variables) to be significant, i.e $Cov(\gamma_{1t-1}, \beta_{it-1}) \neq 0$. However, only a small percentage of the predicted time variation of stock return is explained by their model, leading Ferson and Korajczyk (1995) to admit that the constant beta model for long-horizon returns cannot be rejected. However, they reject a constant beta assumption for the shorter horizon returns over long sample periods. Jagannathan and Wang (1996) explain cross-sectional returns further using the security market line. They find time-varying beta for small, high book-to-market stocks over the business cycle, which largely explains positive unconditional alphas within these stocks. Similar results were found in Lusting and Van Neiuwerburgh (2005) and Santos and Veronesi (2006).

2.8.1 Intertemporal CAPM

Merton (1973) introduced the intertemporal CAPM, which has become a fundamental concept in finance. The intertemporal CAPM predicts a positive intertemporal risk-return relation. As stated in Jiang and Lee (2013), among the approaches to detecting a positive intertemporal risk-return relation is the use of conditional variance as detailed above. Other methods include those that include a hedge component within the empirical specification, as used in Guo and Whitelaw (2006). This method is consistent with the original specification of Merton’s (1973) intertemporal CAPM. The last method originated from Ludvigson and Ng (2007), who argue that the use of a small amount of conditioning information in modelling conditional mean and conditional volatility is the source of empirical disagreements in the risk-return relationship.

The Merton (1973, 1980) intertemporal CAPM can be stated without the hedge component as follows:

$$E\left[\left(R_{M,t} - R_{f,t}\right)|\Omega_{\mathrm{t-1}}\right] = \mu + \gamma E\left(\sigma_{M,t}^{2}|\Omega_{\mathrm{t-1}}\right) \quad (2.18)$$

where

E = The expectations operator

Ω_{t-1} = Information set available at $t-1$

γ = Parameter reflecting the relative risk aversion.

Merton (1973, 1980) found that the expected excess return on the market portfolio, $E\left[\left(R_{M,t}-R_{f,t}\right)|\Omega_{t-1}\right]$, is positively related to the conditional market volatility $\gamma E\left(\sigma_{M,t}^{2}|\Omega_{t-1}\right)$. By collecting terms and adjusting for the near impossibility of reproducing the information set used by economic agents, as stated in Jiang and Lee (2013), we use smaller information set I_{t-1} and rewrite Equation 2.18 as:

$$E\left[\left\{\left(R_{M,t}-R_{f,t}\right)-\mu-\gamma\sigma_{M,t}^{2}\right\}|I_{t-1}\right]=0 \qquad (2.19)$$

Expected market return depends not only on the conditional variance of the market return but also on the covariance with the time-varying future investment opportunity, *i.e.* the hedge component, as shown in the original intertemporal CAPM of Merton (1973). The importance of this hedge component is emphasised in Scruggs (1998). To check for robustness with a hedge component, Jiang and Lee (2013) added four state variables: default risk, term spread, detrended risk-free rate and the dividend-price ratio. They found a strong positive relation between expected excess return and the conditional variance, supporting the findings in Merton (1973). They, however, suggested that the best way of measuring expected excess return and conditional variance is by using the common information set based on a bivariate model of time series of excess return and variance in a consistent manner. They also measure the conditional variance using a bivariate moving average representation of excess returns and variance among other available measures.

2.8.2 Bull and bear beta

Another concept that has had less attention is the use of asymmetric betas, i.e. estimating beta for bull and bear markets, respectively, as stated in Chong, Pfeiffer and Phillips (2011). Chong, Halcoussis and Phillips (2012) support the estimation of dual beta by explaining that single beta estimates of stocks or mutual funds for both upturns and downturns in the market lead to incorrect estimates of beta, as it oversimplifies the risk characteristics of the investment. They explain that data used in estimating a single overall beta can be split into two subsets within the dual-beta model. These two subsets will represent the up-market and down-market, giving rise to two estimates of beta that capture different levels of market risk.

The dual-beta model in Chong, Halcoussis and Phillips (2012) is represented as

$$\left(r_j - r_f\right)_t = \alpha_j^+ D + \beta_j^+ \left(r_m^+ - r_f\right)_t D + \alpha_j^- (1 - D) + \beta_j^- \left(r_m^- - r_f\right)_t (1 - D) + \varepsilon_t, \qquad (2.20)$$

Estimated parameters for up- and down-market days are represented as α_j^+, β_j^+, α_j^- *and* β_j^-, respectively. Dummy variable D is 1 when the market index daily return is non-negative and zero otherwise, $r_m^+ = r_m$ when the market index did not decline and $r_m^- = r_m$ when it does. Others who investigated the dual CAPM include Fabozzi and Francis (1977), Bhardwaj and Brooks (1993), Howton and Peterson (1998) and Faff (2001).

2.9 Higher-order moments

A question posed to asset-pricing models has become: does the traditional mean-variance (two-moment) approach capture the true risk of the distribution of returns? This has become a renewed source of criticisms of the CAPM, with authors insisting that return distribution must account for investor preference for positive skewness and aversion to high kurtosis. The behaviour of stock-market returns departing from the frequently assumed normal distribution has been widely documented, as in Hwang and Satchell (1999), Bates (1996), Jorion (1988) and Harvey and Siddiqui (1999, 2000). Three characteristics universally recognised in time-series returns on assets are clustering in the volatility dynamics, negative skewness and severe excess kurtosis. The phenomena of volatility clustering has been successfully captured in Engle's (1982) class of ARCH models, while the stylised facts of negative skewness and severe excess kurtosis in stock-market returns have remained indisputable.

Using robust measures of skewness and kurtosis and carrying out an extensive Monte Carlo simulation, Kim and White (2004) find that the skewness measures of the S&P500

index are quite close to zero; thus they conclude that there is little skewness in the distribution of the S&P500 index.

However, they also found that, as in the conventional measure of kurtosis, the robust measure indicated excess kurtosis, but in a milder form than previously believed. They also found that removing outliers reduces both conventional measures of skewness and kurtosis substantially, but only very little change to the robust measures. Thus, they conclude that there is no negative skewness and quite mild kurtosis. Hence the robust measures are qualitatively the same, thus refuting the stylised facts previously regarded as true in finance. Bonato (2011) agrees, but emphasises the need for further investigation. In the African market, Omran (2007) found skewness to play a significant role in the return dynamics of the Egyptian stock market.

The debate still rumbles on, with Hung (2008) insisting that higher-order CAPM does not provide a greater return predictive ability than the linear CAPM. However, he does admit that it does provide significant explanatory ability with regards to ex-post time variations. DeMiguel and Nogales (2007) and Breanan and Xia (2001) agree and point to parameter uncertainty for explanation, while Lewis (2006) and Paye and Timmermann (2006) point to the possibility of time-varying and unstable predictive relations.

2.10 The risk-free rate

Another problem faced by the CAPM in explaining return variations, especially in African markets, is in selecting the risk-free rate. In estimating the cost of capital across various African countries, Collins and Abrahamson (2006) used the prevailing rate on US Treasury bills at the end of each period as the risk-free rate for each period. Hearn and Piesse (2009) also used UK Treasury bills (one-month UK gilt rate) in their study; however, they adjusted it to take account of the monthly excess return rather than the quoted equivalent annualised rate. In analysing the CAPM and the DCAPM (downside CAPM) within emerging markets, Estrada (2002) used the yield on 10-year US Treasury notes.

A different approach was taken in Cheung, Wong and Ho (1993), who used the end-of-month weighted average interbank call loan rate as the risk-free rate in Taiwan and the monthly average yield of the government and public bonds in Korea. Bekaert, Harvey and Lundbald (2007) ignored currency effects while using the dollar risk-free rate within emerging markets. In analysing the risk-return association of Dhaka Stock Exchange market using CAPM, Hasan et al. (2012) used the T-bills of Bangladesh. The government treasury rates available in most African countries are often greater than the market return obtainable in the stock market, hence some adjustments may be made to use them. Acording to Cheng et al. (2010), many Arabic countries, including those in Africa, do not have an active debt market. Moreover, the monetary authorities in these countries typically do not act independently. Some countries adhere to a strict reading of Islamic Shari'a law that in effect prohibits charging interest on deposits.

In analysing the CAPM in the Egyptian stock market, Omran (2007) used the average annual short-term rate of 7.05%, from whivch he obtained a weekly short-term rate of 0.136%. Given the prevailing use of dollar-based risk-free rates, this study will use the same to ensure the results are comparable to the literature. The risk-free rate of return will be the US 3-months Treasury bill (US3MT=RR), adjusted to obtain weekly short-term rates, as illustrated in Omran (2007).

2.11 The effect of survivorship bias

The consensus in the literature is that survivorship bias generally leads to an overestimation of performance (returns), as stated in Rohleder et al. (2011). This is because the predominant reason for non-surviving firm disappearance is inferior performance, as shown in Malkiel (1995) and Elton et al. (1996). Because of this obvious problem and its relevance, as identified in the literature, many studies on fund performance address the survivorship bias problem. It is important to note early on that the survivorship bias problem not only affects mutual fund performance, but also affects other financial instruments such as hedge funds, as noted in Liang (2000) and ter Horst and Verbeek (2007). Malkiel and Saha (2005) and Eling (2009) found survivorship bias in hedge funds. Survivorship bias has also been found in stocks, as examined in Brown et al. (1995) and Boynton and Oppenheimer (2006).

In addressing the survivorship bias problem, some studies, such as those of Berk and Green (2004), analytically model the survivorship bias structure, while the majority of the fund performance literature deals with survivorship bias empirically. This usually follows a systematic testing of the significance of survivorship bias on a comprehensive real returns data. These are shown in Carhart et al. (2002), who test for the significance of survivorship bias for one of their measures. In also testing for the significance of survivorship bias, Grinblatt and Titman (1989) used quarterly fund holdings within a small fund sample to construct hypothetical returns.

According to Brown et al. (1992), survivorship bias has implications beyond performance measurement. They find that survivorship bias leads to obvious biases in the first and second moments and cross-moments of return, including beta. Brown et al. (1992) also indicate that there are serious implications for empirical tests of asset-pricing models, as survivorship bias induces spurious volatility-return relationships. This is more so for investigations of the so-called pricing anomalies. Brown et al. (1992) admit that it is difficult to devise a means of correcting survivorship bias using a simple adjustment to standard performance. However, they find that a rather simple procedure of using the residual standard deviation to normalise performance measures may provide a performance measure that is relatively robust to this source of misspecification. An important caveat pre-leads this finding and this relates to an assumption that the investigator knows the true parameters of the process.

Another issue in dealing with survivorship bias is in identifying “best practice” in the literature. According to Rohleder et al. (2011), most studies calculate survivorship bias differently, making it difficult to compare the results. In describing an unbiased portfolio, ter Horst and Verbeek (2007) suggested a portfolio consisting of all funds operating at any time during the sample period. This is supported by research in Blake and Timmermann (1998) and Carhat et al. (2002), who insist that this evaluates the historical performance of a portfolio including all funds investors were able to invest in over time. In defining a biased portfolio, Rohleder et al. (2011) identify two subsets of the unbiased portfolio that are used in literature and typically include only survivors.

As seen in the literature, there are alternative ways of conditioning a sample to correct survivorship bias. One commonly used approach that is quite popular in the literature is known as end-of-sample conditioning, as highlighted in Rohleder et al. (2011). As shown in Otten and Bams (2004) and Deaves (2004), end-of-sample conditioning includes all funds/firms existing at the end of a specific sample period as survivors. The second survivor definition refers to full data-conditioning, which refers to funds/firms that existed through the entire sample period, as seen in Blake et al. (1993) and Holmes and Faff (2004). Some studies use both definitions, as seen in Malkiel (1995). As detailed in Rohleder et al. (2011), another methodological difference that exists in the literature is the use of weights in aggregating individual firm returns in a portfolio. Equal-weighting and value-weighting are the two commonly applied methods. Zhao (2005) demonstrates that survivors are typically larger than non-survivors, as also seen in Carhart (1997).

In analysing the economic relations behind survivorship bias, Rohleder et al. (2011) identify the need to analyse the relations between size, performance and survival in detail. The relation between fund size and performance has always remained mixed in the literature, with some studies being in favour of positive relations, as seen in Otten and Bams (2002). Others such as Chen et al. (2004) and Cremers and Petajisto (2009) found a negative relation. Broadly, related literature on the relation between size and performance found the rationale for a negative relation to be liquidity disadvantages or ownership costs, as in Pollet and Wilson (2008), and the rationale for a positive relation to be mainly economies of scale, as in Indro et al. (1999). However, Indro et al (1999) also show some mixed evidence that indicates optimal size beyond which a positive size-performance relation becomes negative. This mixed evidence is also found in Bird et al. (1983), while Droms and Walker (1996) find no significant relation.

Brown and Goetzmann (1995) found a positive relation between survival and size and between survival and returns using a probit model, and modelling fund disappearance as a function of specified variables. This is supported by findings in Elton et al. (1996) and Cameron and Hall (2003). Cameron and Hall (2003) indicate that fund failure is better predicted using excess return relative to a market index rather than gross returns, which is rather predominant in the literature. Cogneau and Hübner (2015) identify that the determinant of survival varies beyond just size or performance and includes factors such as age (as supported by Lunde et al., 1999, and Brown and Goetzmann, 1995), incentive (as in Massa and Patgiri, 2009), expense ratios (as in Bu and Lacey, 2009) and style (as in ter Horst et al., 2001, and Bu and Lacey, 2009).

2.11.1 The magnitude of the survivorship bias

The magnitude of survivorship bias has also remained contentious, with the likes of Grinblatt and Titman (1989) insisting that survivorship bias accounts for only about 0.1% to 0.4% of return each year when measured on a risk-adjusted basis without accounting for fees and transaction costs. Rohleder et al. (2010) show a survivorship bias alpha of +48 basis points yearly, for the equal-weighted US domestic equity mutual fund market between 1993 and 2006. This implies that the passive benchmark will be outperformed on a risk-adjusted basis by the average fund. The corresponding unbiased portfolio has an alpha of −109 basis points yearly, hence a survivorship bias of 157 basis points annually (which is the difference). The results in Grinblatt and Titman (1989) and Deaves (2004) demonstrate that previous studies have reported survivorship bias that has ranged from 1 to 271 basis points annually. However, Rohleder et al. (2010) insist that the different definitions of survivorship bias in these studies, as well as different time periods covered and different datasets, may account for some of these differences, hence making it difficult to compare.

Eling (2009) estimated survivorship bias for hedge funds to be 0.08% per month, which is comparable to other values found in the literature, as seen in Ackermann et al. (1999) and Liang (2000). Eling (2009) also found that survivorship bias and attrition rate are higher for commodity funds than for stocks or bonds, as also seen in Liang (2000). Eling (2009) found survivorship bias of 0.01% and 0.0034% for stocks and bonds, respectively. Ter Horst and Verbeek (2007) report that survivorship bias is more severe in the mutual fund industry than in the hedge fund industry, due to a higher attrition rate, which they estimate as 5% annually for mutual funds and 14% annually for hedge funds. They highlight that mutual fund attrition is low because typically attrition is due to fund termination, i.e. merger or liquidation, as compared to attrition in hedge funds which can be due to liquidation, closed to new investments or voluntary non-reporting by the fund manager. They also identify that most studies attempt to correct for survivorship bias by taking returns into account until the moment the firm/fund disappears. Ter Horst and Verbeek (2007) found survivorship bias to be 2.1% per annum in their sample.

Malkiel and Saha (2005) identify that the survivorship bias in their study is larger than those reported in other studies. Measuring hedge fund bias as the difference between all hedge fund returns and only surviving funds, they reported a survivorship bias of 374 basis points per year. This is higher than the 60–360 basis points per year reported in Brown et al. (1999), Brown et al. (2001), Liang (2000, 2001) and Amin and Kat (2003).

Malkiel and Saha (2005) believe that the reason for the difference may be the different datasets in use across the literature. Liang (2000) specifically finds a 2% survivorship bias per year, which is consistent with the findings in Fung and Hsieh (1998). However, the bias differs across investment styles. Using data from Hedge Fund Research, Inc. (HFR) and Paradigm LDC and TASS Management Limited (TASS), Liang (2000) finds differences in style classification and survivorship bias across styles, with no style significant in HFR and 10 out of 15 styles significant in TASS.

In investigating the effect of survivorship bias and microstructure distortions on asset pricing, Boynton and Oppenheimer (2006) find that these two biases account for a substantial portion of the size, book-to-market value and contrarian anomalies. However, they also identify that although the effects of these biases are substantial, they do not invalidate the anomalies. They find that the momentum premium identified in Carhart (1995) strengthens when these two biases are controlled for. The significance of survivorship bias is also disclosed in Brown et al. (1999), who asks the question – "given a series is subject to some form of survival bias, does the probability of false rejection of temporal interdependence approach one as the period of survival grows to infinity?". They analysed the consequences of survival for studies of temporal dependency in long-term stock-market returns, event studies and other empirical finance applications.

2.12 Chapter conclusion and gaps in the literature

Given the growing importance of the equity markets in the African continent and the perception of high risk within its markets, it is becoming very important to understand the behaviour of its stock-market returns. Previous studies cited in the literature investigated parts of the problem or a few of the markets; however, this is beginning to change as the African equity market continues to improve in importance. From the literature review, it can be argued that there are a considerable number of gaps in our body of knowledge. These issues will be summarised here.

The primary focus of this research will be the African stock markets, due to the relative newness of the market and very sparse asset-pricing research into it. This is particularly important as African stock markets have been found to be thin and illiquid, as seen in Allen et al. (2009) and Allen, Otchere and Senbet (2011), with stocks traded being less than 1% of GDP, as reported in Senbet and Otchere (2010). Even with the highlighted importance of liquidity, most asset-pricing research in the African market does not yet consider the liquidity factor. The importance of liquidity in asset pricing is well documented in Hearn and Piesse (2009). This will be analysed after considering the importance of the Fama-French and Carhart studies. The following research gaps are identified.

Models: To identify which of the Sharpe/Lintner CAPM, Fama-French three-factor model, Carhart four-factor model or their augmented models performs best within the African market. This will naturally lead to the analysis of the importance of the variables in the models within the African context.

Liquidity: Given the importance of liquidity as identified in the literature, the thesis will make a novel contribution in evaluating the importance of liquidity in an African index.

If most African markets are segmented, we expect little or no financial contagion resulting from the financial crisis, apart from the South African market, and perhaps some political contagion resulting from the Arab Spring, as some of the north African countries were affected. The expectation is that contagion can manifest with the asset-pricing model, or can be a reason for structural changes. Structural breaks can also be present because of the introduction of new institutions and also as a result of drastic political or economic policy changes. This will mean that we need not always reject or accept the CAPM for the whole period as the single possible result, as the structural change modelling strategy allows for different dynamic behaviour among different regimes, leading to structural changes. Given the nature of the African markets, I believe that it is more prone to breaks than most markets, hence the following gaps are identified.

Contagion: This research will investigate the impact of contagion on the asset-pricing models.

Structural breaks: This research will fill this gap in the literature by investigating structural breaks within the data.

As identified in the review, African markets are perceived to be unstable due to the evolving degree of market integration, re-emerging and survivorship bias in data, significant non-economic factors such as political factors and the evolution from an emerging/frontier market towards a mature market. Hence the assumption that beta is stable, as indicated by the Sharpe-Lintner CAPM, will be unlikely. Jagannathan and Wang (1996) insist that this assumption is not reasonable as the relative risk of an asset is likely to vary over time. They insist that betas and expected return will, in general, depend on the nature of the information available at any given point in time and vary over time. With the susceptibility of African stocks to shocks, the assumption of a static beta will be most unlikely, hence the following research gap is identified.

Conditional CAPM-type model: This research will fill this gap in the literature by investigating whether conditional information plays a role in determining excess returns in the African market.

With criticisms of the mean-variance approach on its ability to capture the true risk of the distribution of returns, some in the literature insist that return distribution must account for investor preference for positive skewness and aversion to high kurtosis. This will most likely be particularly important in the African market following the findings in Hwang and Satchell (1999), which proposed the use of the four-moment CAPM over the conventional mean-variance CAPM, due to non-stationarity in emerging markets.

Higher-moment CAPM: This research will fill this gap in the literature by comprehensively investigating the explanatory power of the higher-order moments in the African market.

Another very important finding from this review is the fact that survivorship bias has become a major issue, with its impact expected to be more severe in the African market due to relatively high levels of stock disappearance (high attrition rate). Rohleder et al. (2010) show a survivorship bias of 157 basis points yearly for the equal-weighted US domestic equity mutual fund market between 1993 and 2006, while Deaves (2004) finds survivorship bias of between 232 and 271 basis points per year in the Canadian market.

Given the high disappearance of firms in the African market, it is absolutely essential to eliminate survivorship bias from datasets, as it has implications even beyond performance measurement. Indeed, Brown et al. (1992) find that it leads to obvious biases in the first and second moments and cross-moments of return, including beta. This questions asset-pricing studies in the African market, as all studies found so far do not eliminate survivorship bias from their sample.

Survivorship bias: This study will fill this gap in the literature by eliminating survivorship bias from the sample and also identifying the nature of survivorship bias in the African market. This survivorship bias-free dataset will be used within the analysis.

3 DATA DESCRIPTION, INDEX CREATION, METHODOLOGICAL NOTES AND PORTFOLIO FORMATION

3.1 Introduction and structure of the chapter

The deregulation of national markets and the relaxation of capital controls are fuelling the growth in international investment among private and institutional investors. According to Saritas and Aygoren (2005), international diversification has continued to spur international investments due to its ability to yield superior risk-reward trade-off when compared to domestic investments. Early studies by Grubel (1968), Levy and Sarnat (1970) and Solnik (1974) highlight the low correlations between index returns in different countries. However, proponents of international investments recognise that transaction costs can be significantly higher in international markets due to political risks, currency risks, regulatory and cultural differences, and high trading costs, as highlighted in Jorion and Roisenberg (1993). As Saritas and Aygoren (2005) remark, one effective strategy for overcoming the challenges of international investing is international indexing. This leads Griffin and Karolyi (1998) to conclude that the benefits of international diversification outweigh the numerous costs.

This is perhaps more so in the African market, with its high volatility but with a potential for higher average returns when compared with the rest of the world, as noted in Assefa and Mollick (2014). More problems also blight an analysis of asset pricing in the African markets and this mainly relates to data. We identify the problems related to the data and proffer some African market-specific solutions.

This chapter provides a rationale for the index creation, describes the data within the sample and highlights some data issues and remedies. It also identifies the methods to be applied, given the sample and the data available, and explains the portfolio formation process. The chapter starts with the discussion and identification of the research philosophy for this research Section 3.1.1 and the development of the emerging and frontier market indices in Section 3.2. The sample selection and data description are highlighted in Section 3.3, while the methodology and correction of survivorship bias are shown in Section 3.4. The total returns index formation is discussed in Section 3.5, while Section 3.6 makes the case for the consideration of the financial crisis and the Arab Spring events in a contagion-based analysis. Diagnostics are reported in Section 3.7, while Section 3.8 analyses the methodological approaches available for the modelling procedures and highlights the empirical models.

Various measures of skewness and kurtosis are analysed in Section 3.8.3 while Section 3.8.4 identifies the tests for structural breaks. The GARCH-type conditional CAPM methods are identified in Section 3.8.5, while Section 3.8.6 identifies other potential alternative methods, which include the threshold CAPM, the Kalman filters, the stochastic volatility conditional betas and the Markov switching approach. Following the discussions, the empirical models to be used are highlighted in Section 3.9, which also includes the formation of portfolios. Section 3.10 and 3.11 are the chapter conclusion and chapter appendices respectively.

3.1.1 Philosophy of science

"Methodological understanding of theory is as important as theory itself, and must show the relationship between theoretical concepts used in the study and its expected conclusions" – Justine George (2016, p1).

It has long seemed that among social sciences, especially in the realms of economics and sociology, so much time has been spent in discussing the methodological aspects of theory. The measurement of how scientific a theory is and its categorisation based on its relative merit can be difficult, given available theories. However, major theoretical contributions seem to be those of Karl Popper, Thomas Kuhn and Imre Lakatos, which are the best in developing a framework for the evaluation of progress in social science research.

The core of the arguments from Karl Popper are identified in his core texts – Popper (1957, 1959, 1963 and 1972). Popper identified that science begins with problems and then proceeds via "conjecture and refutation". He also identified that scientists propose bold theories that are then tested and if falsified, they are given up. He insisted that science then becomes made up of testable as-yet-unfalsified theories and that pseudoscience is immune to criticism. Kuhn (1964), on the other hand, argued against the points made by Popper by insisting that normal science is conducted within paradigms, which are gradually extended via puzzle-solving. The paradigm could be referred to as a researcher's social identity, which relates to agreements among groups of scientists about methods, theories and assumptions that relate to the "world", that they agree upon and never question. Puzzle-solving relates to the quest of researchers within each paradigm to extend the reach of the paradigm, but not really test it or question its central ideas/methods.

With regards to Popper's claim that science is made up of testable yet falsifiable theories and that only pseudoscience is protected from criticism, this implies that a theory must have the capability to be falsified to be termed scientific. Kuhn disagrees as he insists that scientific knowledge is protected from criticism because it is characterised as part of a paradigm, and scientists never question those paradigms. Kuhn believes that changes in paradigms will only happen very rarely in a "revolutionary paradigm shift" where science breaks out from one paradigm to another. Kuhn remains very popular in social sciences as he believes in picking a paradigm and using theory as lenses not to be tested or criticised. Here the activity involved in the research becomes one of puzzle-solving and not theory-testing. Popper, on the other hand, seems to be more popular within natural sciences where theories are tested, maybe rejected and maybe modified. This is done through testing and rejecting a null hypothesis with the logic being more of conjecture and refutation.

Lakatos proposed the "methodology of scientific research programmes", which was proposed specifically to address Popper's insistence on the fundamental importance of subjecting scientific theories to persistent and ruthless empirical refutations, and to Kuhn's insistence on the importance of preserving accepted paradigms from refutation. The Lakatos framework examines scientific research, which is useful in evaluating a series of theories to judge whether theoretical development in a particular stream is "degenerating" or "progressing". The proposal of Lakatos incorporates elements of Popper and Khan. To know whether a theory is science, Lakatos highlights that it is necessary to know its history. If it has been arrived at by content-reducing, ad hoc modifications of earlier theories, in the face of anomalies then it is not scientific. If it is a series of theories, that are referred to as a research programme, then it is scientific.

The research programme identified by Lakatos comprised a “negative heuristic” and a “positive heuristic”. The negative heuristic specifies the “hard core” of the programme, which is its conceptual framework or its metaphysical foundation. This hard core cannot be refuted by the methodological fiat of the programme’s proponents. The negative heuristic of the programme functions to prevent any anomalies that may occur from refuting the hard core. This is done by directing the scientists’ attention to the revision of the “protective belt” of supplementary hypothesis and initial conditions. The procedure to modify the protective belt is specified by a partially articulated plan – the positive heuristic.

Lakatos identified two conditions for the successful modification of a protective belt of a research programme. The first relates to each successive modification being “theoretically progressive” or having “excess empirical content”, where the new theory, which is made up of laws of nature, auxiliary hypothesis and initial conditions, must predict some previously unexpected new fact. The second condition relates to the fact that the modifications must be “empirically progressive”, as the predicted fact must be at least occasionally substantiated. The converse relates to a “degenerating” programme, where it is not “progressive”. According to Lakatos, a research programme must be at least theoretically progressive to be regarded as scientific. For one research programme to surpass a rival, the rival must be degenerating while it is progressive. Also, it must successively explain the previous predictive success of its rival.

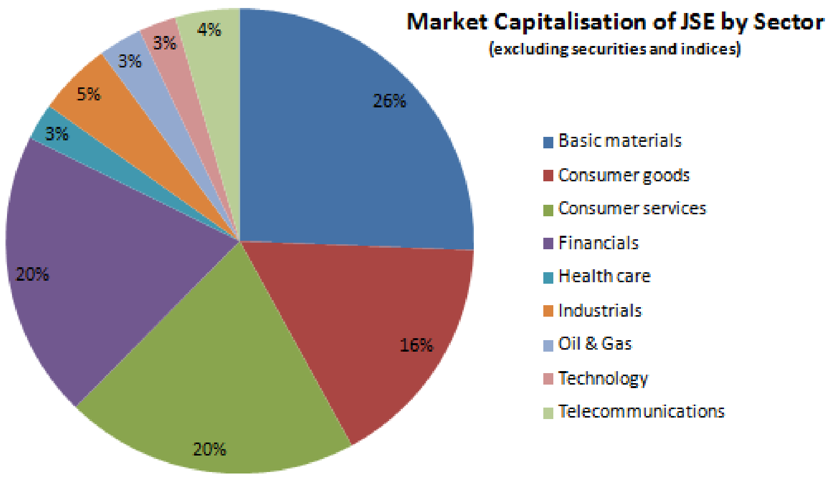
The research carried out within this thesis follows the principals of Lakatos, as there are core theories that are protected and have a protective belt upon which the research is based. The hard core of the research relates to theories such as the portfolio theory (Markowitz, 1959) and Tobin’s liquidity preference (Tobin, 1958). The protective belt relates to the CAPM (Sharpe, 1964, and Lintner, 1965), three-factor model (Fama and French, 1992, 1993), four-factor model (Carhart, 1997), importance of liquidity (Hearn and Piesse, 2009), importance of higher moments (Chiao, Hung and Srivastava, 2003), impact of contagion (Bekaert, Harvey and Ng, 2005) and conditional CAPM (Jagannathan and Wang, 1996).

3.2 Development of the emerging and frontier African market indices

As identified earlier, formation of these indices is essential due to the relative paucity of data in the African market; hence the index provides some diversification benefits that mimic an ideal investor's behaviour when investing in a risky asset. The stock market in Africa remains the smallest of any region despite the surge in the establishment of stock exchanges, particularly in Sub-Saharan Africa, in the last two decades. The riskiness of the African market is further highlighted by the relatively high illiquidity of stock in the continent, with East African stocks trading being less than 1% of GDP, as noted in Senbet and Otchere (2010). The use of indices will not entirely eradicate this problem, but will make stocks on the continent more tradable.

To ensure the benefits of diversification, a resource-driven (basic materials sector) index is formed. The index is formed using stocks in the basic materials index because most African countries are resource-driven. For example, the basic materials stocks form about one-quarter of the capitalisation of the Johannesburg Stock Exchange's (JSE) average capitalisation (data as at 4 February 2013, via Forbes, 2014), making it the largest component of the JSE.

Figure 3.1 Market capitalisation of the Johannesburg Stock Exchange by sector



Collins and Abrahamson (2006) also identify the resources sector as the largest in South Africa. According to Hearn (2011), resource-driven stocks in Egypt and Morocco form about 38.4% and 15.3% of the total market capitalisation, respectively. This suggests that a sample index formed on the basic materials index will to a large extent be representative of the overall emerging African market.

To capture the risk-return behaviour in this sector, I will form the sample for this research on the classification of the African market into emerging and frontier African markets, as identified in the FTSE quality of market criteria (AFRICA) as at March 2014. It classified South Africa as an advanced emerging market, while Egypt and Morocco were classified as emerging and, for the purpose of this research, South Africa, Egypt and Morocco will be classified as emerging. The following countries were classified as frontier markets: Botswana, Cote d'Ivoire, Ghana, Kenya, Mauritius, Nigeria and Tunisia. The weightings for each market in the indices are analysed in each portfolio formation section. Although FTSE has made this classification, it has not formed any index using the resource stocks in these African countries. This also applies to the MSCI indices. Hence I form indices based on the basic materials index, initially for the emerging African market and subsequently for the frontier African market.

Also, the use of indices improves informational efficiency when compared to individual national stock prices indices, as identified in Ntim et al. (2011). They also identify that individual national indices in the African continent are weak-form inefficient, while some efficiency can be achieved in countrywide stock-price indices.

Apart from mimicking a diversification strategy, these indices are formed to alleviate some of the data problems identified in Section 3.1.1.

3.3 Sample selection and data description

3.3.1 Emerging African market[16]

As identified earlier, the selection of countries in the emerging Africa index followed the classification in the FTSE quality of market criteria (AFRICA), as at March 2014. It classified South Africa as an advanced emerging market, while Egypt and Morocco were classified as emerging and, for the purpose of this research, South Africa, Egypt and

[16] The stocks identified within each market are based on end-of-sample conditioning, hence will have a survivorship bias problem. This will be corrected in Section 4.4.

Morocco will be classified as emerging. The basic materials indices were selected from each country, as most African countries economies are resource-driven. In South Africa, the basic materials index (.JBASM) was selected, and comprised 19 firms as at 01/01/2015, as shown in Table 3.1.

Table 3.1 Sample selection from the South African stock market: The basic materials index[17]

Name	**RIC**	**Sector - ICB**	**Mcap (USD)**
Sasol Ltd	SOLJ.J	Speciality chemicals	23,015,656,598.98
Mondi Ltd	MNDJ.J	Paper	9,656,459,345.23
Nampak Ltd	NPKJ.J	Paper	9,656,459,345.23
AngloGold Ashanti Ltd	ANGJ.J	Gold mining	7,977,034,421.24
Anglo American Platinum Ltd	AMSJ.J	Platinum & precious metals	7,174,859,064.07
Kumba Iron Ore Ltd	KIOJ.J	Iron & steel	4,505,004,425.81
Gold Fields Ltd	GFIJ.J	Gold mining	3,495,450,013.82
Impala Platinum Holdings Ltd	IMPJ.J	Platinum & precious metals	3,182,320,793.86
African Rainbow Minerals Ltd	ARIJ.J	General mining	1,926,159,303.79
Assore Ltd	ASRJ.J	General mining	1,739,658,463.81
AECI Ltd	AFEJ.J	Speciality chemicals	1,382,484,844.35
Omnia Holdings Ltd	OMNJ.J	Speciality chemicals	1,029,028,738.38
Pretoria Portland Cement Ltd	PPCJ.J	Cement and concrete	949,890,841.04
Royal Bafokeng Platinum Ltd	RBPJ.J	Platinum & precious metals	842,427,310.12
Harmony Gold Mining Company Ltd	HARJ.J	Gold mining	834,725,797.33
ArcelorMittal South Africa Ltd	ACLJ.J	Iron & steel	831,295,777.97
Mpact Ltd	MPTJ.J	Paper	576,132,429.34
African Oxygen Ltd	AFXJ.J	Speciality chemicals	370,559,105.72
Eqstra Holdings Ltd	EQSJ.J	Mineral resources	143,670,341.44

In Egypt, the basic material index (.TRXFLDEGPMAT) was selected, which comprised 10 firms as at 01/01/2015, as shown in Table 3.2.

[17] Source: Reuters Eikon and Datastream

Table 3.2 Sample selection from the Egyptian stock market: The basic materials index[18]

Name	RIC	Sector - TRBC	Mcap (USD)
Suez Cement Company SAE	SUCE.CA	Cement & concrete manufacturing	977,210,588.07
Ezz Steel Co SAE	ESRS.CA	Iron & steel	969,048,101.90
SidiKerir Petrochemicals Co SAE	SKPC.CA	Commodity chemicals	963,990,825.69
MisrBeniSuef Cement Co SAE	MBSC.CA	Mining	412,844,036.70
South Valley Cement Co SAE	SVCE.CA	Cement & concrete manufacturing	355,214,081.36
Misr Cement Co ESC	MCQE.CA	Mineral resources	324,977,093.05
Sinai Cement Co SAE	SCEM.CA	Cement & concrete manufacturing	287,247,706.42
Egyptian Chemical Industries SAE	EGCH.CA	Agricultural chemicals	233,946,720.35
Paints and Chemical Industries Co SAE	PACH.CA	Chemicals	132,372,214.94
Egyptian Financial and Industrial SAE	EFIC.CA	Agricultural chemicals	81,018,421.68

In Morocco, the basic material index (.TRXFLDMAPMAT) was selected, which comprised six firms as at 01/01/2015, as shown in Table 3.3.

Table 3.3 Sample selection from the Moroccan stock market: The basic materials index[19]

Name	RIC	Sector - TRBC	Mcap (USD)
Lafarge Ciments SA	LAC.CS	Cement & concrete manufacturing	3,300,066,402.77
Ciments du Maroc SA	SCM.CS	Mineral resources	1,690,232,798.38
Holcim Maroc SA	HOL.CS	Cement & concrete manufacturing	1,186,055,315.80
Managem SA	MNG.CS	Diversified mining	917,947,211.73
Societe Metallurgique du Meter SMI	SMI.CS	Diversified mining	489,099,889.66
Touissit Cie Miniere de SA	CMT.CS	Lead ore mining	217,802,105.07

[18] Source: Reuters Eikon and Datastream

[19] Source: Reuters Eikon and Datastream

The market portfolio includes South Africa's JSE All Share Industrials index, Egypt's EGX 100 Index and Morocco's Casablanca SE All Share Index. The risk-free rate of return is the US 3-month Treasury bill (US3MT=RR) adjusted to obtain weekly short-term rates, as illustrated in Omran (2007). This represents the risk-free rate adjusted to take account of weekly excess returns rather than the quoted equivalent annualised rates. The US risk free rate is used to ensure that the study is comparable to studies in the African market, like those of Collins and Abrahamson (2006) and Bekaert, Harvery and Lundbald (2007). See Section 2.10 for further justification.

3.3.2 Frontier African market

The selection of countries in the frontier Africa index followed the classification in the FTSE quality of market criteria (AFRICA), as at March 2014. The constituents of the frontier African market index are Botswana, Cote d'Ivoire, Ghana, Kenya, Mauritius, Nigeria and Tunisia. However, because of the paucity of data, Ghana and Mauritius will be excluded. The resource indices were selected from each country as most African countries' economies are resource-driven.

In Botswana, the basic materials index (.FCIBT) was selected, and comprised eight firms as at 01/01/2015, as shown in Table 3.4.

Table 3.4 Sample selection from the Botswana stock market: The basic materials index[20]

Name	RIC	Sector - TRBC	Mcap (USD)
Discovery Metals Ltd	DML.BT	Copper ore mining	8,942,875.36
CIC Energy Corp	ELC.BT	Coal	53,051,485.62
Investec Ltd	INV.BT	Diversified investment services	7,929,081,318.21
Decimal Software Ltd	AVA.BT	Diversified mining	11,155,855.88
A-Cap Resources Ltd	ACB.BT	Uranium mining	13,785,131.38
African Copper PLC	ACU.BT	Copper ore mining	10,407,353.74
Anglo American PLC	AGLO.BT	Diversified mining	26,111,188,090.19

[20] Source: Reuters Eikon and Datastream

On the BRVM in Cote d'Ivoire, the Industrials index (.INDCI) was selected, and comprised four firms as at 01/01/2015, as shown in Table 3.5.

Table 3.5 Sample selection from the Abidjan stock market: The basic materials index[21]

Name	RIC	Sector - TRBC	Mcap (USD)
Vivo Energy Cote d'Ivoire SA	SHEC.CI	Oil & gas refining and marketing	145,680,215.99
Air Liquide Cote d'Ivoire SA	SIVC.CI	Commodity Chemicals	27,585,322.81
Total Cote d'Ivoire SA	TTLC.CI	Gasoline stations	419,827,944.60
Petro Ivoire SA	MLPIV.PA	Oil & gas refining and marketing	18,989,454.94

In Kenya, the basic material index (.EPNR) was selected, which comprised three firms as at 01/01/2015, as shown in Table 3.6.

Table 3.6 Sample selection from the Nairobi stock market: The energy and petroleum index

Name	RIC	Sector - TRBC	Mcap (USD)
Kenya Electricity Generating Co Ltd	KEGN.NR	Renewable utilities	248,182,478
Kenya Power and Lighting Company Ltd	KPLC.NR	Electric utilities	313,185,081.93
KenolKobil Ltd	KENO.NR	Oil & gas refining and marketing	143,348,074.82

In Nigeria, the NSE Oil and Gas index (.NGSEOILG5) was selected, which comprised seven firms as at 01/01/2015, as shown in Table 3.7.

[21] Source: Reuters Eikon and Datastream

Table 3.7 Sample selection from the Nigerian stock market: The NSE oil and gas index[22]

Name	RIC	Sector - TRBC	Mcap (USD)
Oando Plc	OANDO.LG	Integrated oil and gas	781,195,016.34
Total Nigeria Plc	TOTAL.LG	Petroleum product wholesale	264,526,308.22
Mrs Oil Nigeria Plc	CHEVRON.LG	Petroleum product wholesale	73,877,514.22
Conoil Plc	CONOIL.LG	Petroleum product wholesale	143,341,545.69
Forte Oil Plc	FO.LG	Petroleum product wholesale	1,346,068,644.73
Seplat Petroleum Development Company Plc	SEPLAT.LG	Oil and gas exploration and production	1,122,381,953.12
Mobil Oil Nigeria Plc	MOBIL.LG	Petroleum product wholesale	311,503,834.86

In Tunisia, the following six firms will be used, as shown in Table 3.8.

Table 3.8 Sample selection from the Tunisian stock market[23]

Name	RIC	Sector - TRBC	Mcap (USD)
Ste Sotuver SA	STVR.TN	Glass Containers & Packaging	61,736,046.76
Ste Chimique Alkimia SA	ALKM.TN	Commodity Chemicals	61,612,016.41
Sotipapier SA	STPAP.TN	Paper Mills and Products	64,219,445.49
Air Liquide Tunisie SA	AL.TN	Commodity Chemicals	165,373,609.70
Manufacture de Panneaux Bois du Sud SA	MPBS.TN	Wood Products	24,126,719.69
Industries Chimique de Flour SA	ICF.TN	Commodity Chemicals	42,088,807.85

3.3.3 Data problems

Missing data points are a major problem within the African market (see also Chapter 2, Section 2.4). Within different sector indices, I observe missing data points that result from thin trading and sometimes no trading in some markets. I take a few precautions to ensure that the study is robust in the presence of data problems. The use of the basic materials index alleviated some of this problem as the resource sector remains the largest within

[22] Source: Reuters Eikon and Datastream

[23] Source: Reuters Eikon and Datastream

the African continent and subsequently the most traded. To harness the benefits of diversification and to minimise the impact of the data problems identified, this study will be based on an index of emerging African markets and frontier African markets. Section 3.9.1 below highlights the formation procedure for these indices.

Also, I found that most stocks traded daily but some did not, and in these cases I found that my use of a weekly data point could eliminate the impact of this problem. The trading week in some African countries is from Sunday to Thursday, which can potentially create a problem in aligning returns weekly. I take the approach of a weekly returns window, where the end of the trading week is aligned, rather than a particular day in the week, as long as the difference is by only a day. Another potential problem relates to survivorship bias as was found within the emerging African market in Chapter 4 and highlighted in the literature review in Chapter 2. As seen in Section 2.11 of the review, the evidence suggests that survivorship bias is a major problem within African markets and will bias estimates of the risk-return relationship, first and second moments as well as cross-moments of returns. In eliminating survivorship bias, I follow the procedure identified in Section 3.4.2. The formation of the emerging and frontier African market index also ensures that there are sufficient data points for portfolio formation throughout the sample period, as I take a multi-country market index dimension rather than a single country dimension because of the problems identified above.

3.4 Survivorship bias

Following the discussions in Section 2.12 of Chapter 2, I identify two potential methods of correcting survivorship bias and report the number of stocks in the survivorship bias-corrected sample compared with the biased sample.

3.4.1 Heckman's two-equation method

To neutralise the effect of selection bias resulting from selecting survivors using end-of-sample conditioning, one of the most common methods in literature is the Heckman two-equation method. Heckman (1979) uses a binary approach that depends on a linear combination of observable and unobservable factors, as identified in Tucker (2010). This approach estimates the choice model in stage one, and in stage two a bias correction term is added to the regression. This bias correction variable in the form of an inverse Mills ratio (IMR), is derived after further restricting unobservables to multivariate normal distributions. Because of the use of truncated binormal distribution in deriving the IMRs, the appropriate approach will be to model the first-stage choice decision in binary probit, and the second stage in a linear regression, and if the unobservables in the two stages are binormally distributed. As noted in Tucker (2010), adding IMR to the second stage does not correct the selection bias if these conditions are not met. However, Michaely, Rubin and Vedrashko (2015) insist that the Heckman two-equation model could reduce the extent of the bias but not fully eliminate it, hence it will not be used in this study.

3.4.2 CRSP methodology

The CRSP database is renowned for providing survivorship-bias-free data for research in security pricing. The database originated developed by Mark M. Carhart for his 1995 dissertation, *Survivor Bias and Persistence in Mutual Fund Performance*. According to the methodology detailed in crsp.com, the “M” funds (dead funds) are introduced into the dataset so as to eliminate survivorship bias. Although the CRSP database is quite accurate, it actively seeks to correct some known biases as they are found, as identified by CRSP.

One of the major biases is a returns averaging bias resulting from a situation where a split in a fund results in, say, four other funds and each new share class of fund is permitted to inherit the entire return history, resulting in the duplication of returns histories. The second bias is a selection bias that favours the best performing private funds when they become public. This is because the SEC has started permitting funds with prior returns histories as private funds to splice these returns onto the beginning of their public histories. This will mean that only successful private find histories will be added to the database.

As stated in Gottesmann and Morey (2007) and Rohleder et al. (2010), the CRSP database only provides survivorship-bias-free data for the US mutual fund market, whereas for many other countries such comprehensive data is not available.

The CRSP methodology will, however, be applied to our dataset but with some further adjustments. The “dead” firms in our case will include delisted firms and firms that have gone private, merged, along with bankrupt/liquidated firms; hence some of the firms may come back into the dataset, if they are only removed from the index at any one time for any reason apart from liquidation. According to Blake and Timmermann (1998) and ter Horst and Verbeek (2007), an unbiased portfolio consists of all funds operating at any time during the sample period (as at when they are on the index in the case of a firm). According to this definition, a portfolio that does not include new firms is not unbiased.

Hence the dataset for this study will include all firms in the index for the length of time they were on. This will be referred to as the unbiased dataset. To analyse the effect of survivorship bias, the unbiased dataset will be compared to the end-of-sample survivors for the emerging African market and the South African market. Details of the dataset will be discussed in the data chapter.

3.4.3 Correction for survivorship bias

As identified above, correction for survivorship bias will take the form of the CRSP methodology. This will be applied to our dataset but with some further adjustments. The “dead” firms in our case will include delisted firms and firms that have gone private, merged, along with bankrupt/liquidated firms, hence some of the firms may come back into the dataset, if they are only removed from the index at any one time for any reason apart from liquidation. According to Blake and Timmermann (1998) and ter Horst and Verbeek (2007), an unbiased portfolio consists of all funds operating at any time during the sample period (as at when they are on the index in the case of a firm).

Following this, the number of companies for the unbiased and biased samples of the emerging and frontier African markets are detailed below.

3.4.3.1 Unbiased dataset (survivorship bias corrected) – emerging African market index

The number of firms in the unbiased dataset of the emerging African market (the basic materials sectors of South Africa, Egypt and Morocco) is shown below.

Table 3.9 Number of companies in the unbiased emerging African market[24]

2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004
40	47	51	56	63	65	61	60	65	50	35

Data on some delisted firms have been removed from the database and hence will not be used in this study. They are excluded as they have insufficient data to be considered. The firms are: South Africa – Gold One International (GDOJ.J), Freeworld (FWDJ.J), Eland Platinum (ELDJ.J), Uranium (UUUJ.J); Egypt – HAC (HACCO.CA), AMCC (AMRI.CA).

3.4.3.2 The biased dataset – emerging African market index

The number of firms in the end-of-sample conditioned dataset of the emerging African market (the basic materials sectors of South Africa, Egypt and Morocco) is shown below.

Table 3.10 Number of companies in the biased emerging African market[25]

2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004
35	35	35	35	35	35	35	35	35	35	35

3.4.3.3 Unbiased dataset (survivorship bias corrected) – frontier African market index

The number of firms in the unbiased dataset of the frontier African market (the basic materials sector of Botswana, Cote d'Ivoire (which consists of Benin, Burkina Faso, Guinea Bissau, Cote d'Ivoire, Mali, Niger, Senegal and Togo), Kenya, Nigeria and Tunisia, is shown below.

Table 3.11 Number of companies in the unbiased frontier African market[26]

2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004
25	24	24	23	23	23	20	17	16	15	15

[24] Source: Reuters Eikon and Datastream

[25] Source: Reuters Eikon and Datastream

[26] Source: Reuters Eikon and Datastream

3.4.3.4 The biased dataset – frontier African market index

The number of firms in the end-of-sample conditioned dataset of the frontier African market (the basic materials sector of Botswana, Cote d'Ivoire (which consists of Benin, Burkina Faso, Guinea Bissau, Cote d'Ivoire, Mali, Niger, Senegal and Togo), Kenya, Nigeria and Tunisia, is shown below.

Table 3.12 Number of companies in the biased frontier African market[27]

2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004
25	25	25	25	25	25	25	25	25	25	25

3.5 Total return index formation

The emerging and frontier Africa indices are formed following mostly the methods used by the FTSE group of indices and the International Organisation of Securities Commission (IOSCO). The return on these indices is the weekly return using the closing price of the last day of the trading week. This total return index is based share price data from Reuters/DataStream which are adjusted for dividends, preference shares, loan stock and splits (capital changes). The prices are based on the firms' home country currency, but only the calculated (logarithm) returns are used within the index.

For the purpose of the indices to be formed, eligible securities are all securities within the specified country. For the emerging Africa market index, the companies within the specified sector are those that have a full listing on the Casablanca Stock Exchange, the Egyptian Stock Exchange and the Johannesburg Stock Exchange. For the frontier African market index, the companies are those that have a full listing on the Botswana Stock Exchange, the BRVM, the Nairobi Stock Exchange, the Nigerian Stock Exchange and the Tunisian Stock Exchange.

The securities will be tested for liquidity yearly by calculating the median weekly trading per quarter. When calculating the median of weekly trades per quarter of any security, a minimum of five trading weeks in each quarter must exist, otherwise the quarter will be excluded from the test. Following the methodology in the FTSE, liquidity will be tested for the June review from the first business week of the quarter, at the start of April. The calculation of the median trade is done by ranking the weekly trade and selecting the

[27] Source: Reuters Eikon and Datastream

middle ranking week. Zero trading weeks are included in the ranking, such that any security that does not trade for more than half the weeks in the quarter will have a median weekly trade of zero.

According to the Egyptian Stock Exchange, trading is from Sunday to Thursday; hence the end of the trading week will be aligned to the end of the trading week for Morocco and South Africa, both of which trade from Monday to Friday, for the emerging African market.

For the frontier African market, trading is from Monday to Friday on the Botswanan, Kenyan (Nairobi), Nigerian and Tunisian stock exchanges, while trading is on Monday, Wednesday and Friday on the BRVM.

The initial constituents of the index are the constituents of each individual country's index as at 01/01/2015. However, this changes throughout the period as the sample is adjusted to eliminate survivorship bias (details are given in Section 3.4). The constituents of each of the countries' index must be classed as being part of the basic materials index by Reuters for each country as at 01/01/2015. The indices' algorithm and calculation method is based on the returns of the different basic materials indices that form the emerging and frontier Africa index, hence the asset returns index series is calculated using the following average return (AR) formula:

$$\frac{\sum_{i=1}^{n}(r_i)}{n}$$

where,

i = 1,2,….,n

n is the number of basic materials indices in the index.

r_i is the returns on each basic materials index (returns calculated using the price at the close of the week)

The index returns are calculated based on the arithmetic average of the returns of the individual indices, which implies rebalancing to equal weights for each period. Blume and Stambaugh (1983), Roll (1983) and Conrad and Kaul (1993) used an equal-weighted buy-and-hold return for the benchmark portfolio to minimise the impact of compounding related bias. Bartholdy and Peare (2005) found that an equal-weighted index provides the best estimate compared to the commonly recommended value-weighted index. This study uses weekly equal-weighted returns. Following Bartholdy and Peare (2005), no adjustments were made for dividends. Data from Reuters/Datastream are, however, already adjusted for dividends.

3.6 Contagion – the financial crisis and the Arab Spring

According to Pettenuzzo and Timmermann (2011), beyond the risks of the components of stock return not being predicted by any model of return-generating process, parameter uncertainty and uncertainty as to the function form of the true return process, investors also face model instability risk, which refers to "breaks" in the parameters of the return-generating process. Normal practices assume that model parameters remain constant over time. This ignores the fact that estimation samples often span years and sometimes decades, hence the relationship between economic variables will likely not remain the same. Instabilities in these economic variables could result from technological, legislative or institutional change, tax policy, monetary targets, large macroeconomic shock, financial innovation, financial crisis and political factors.

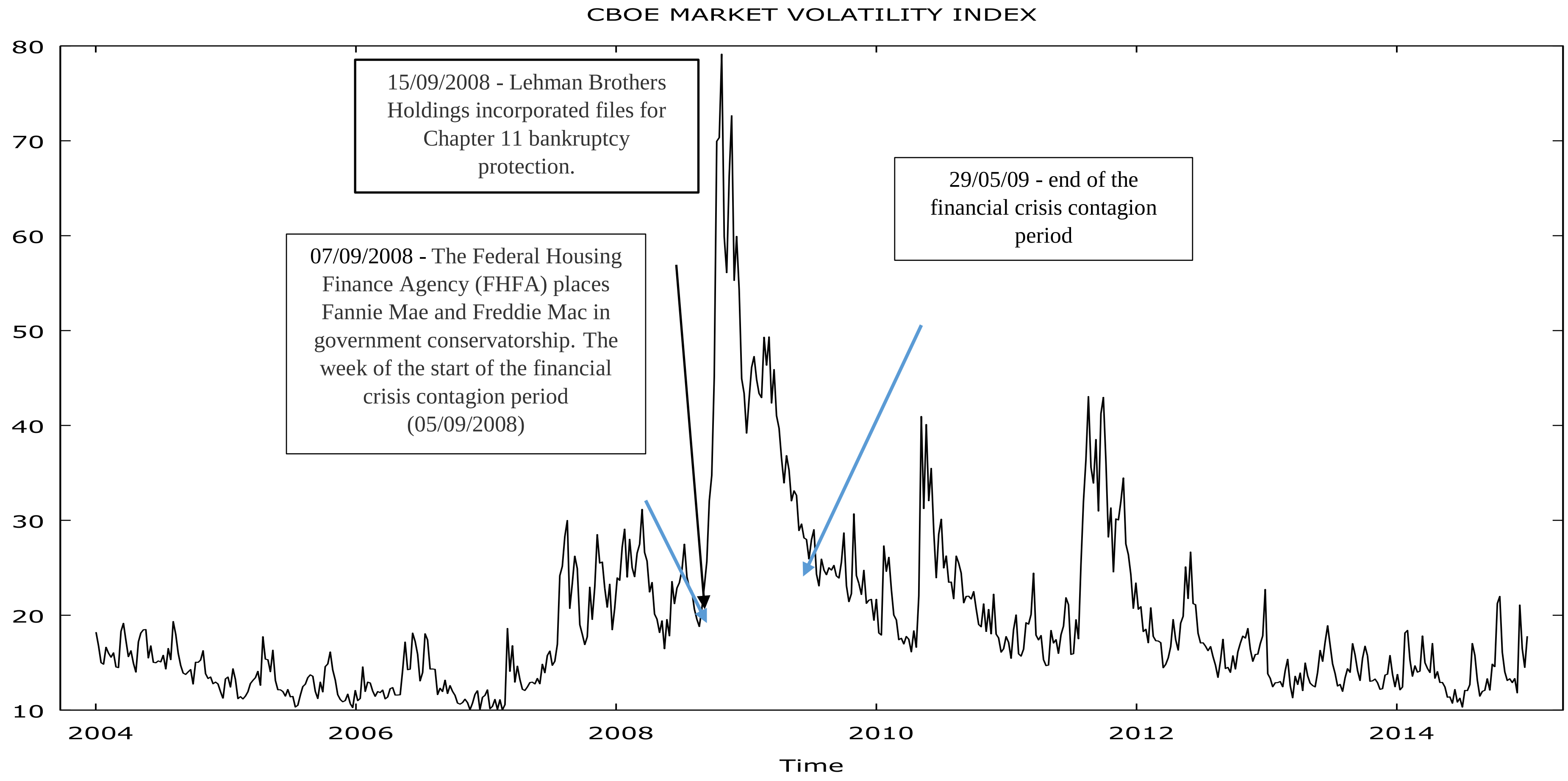
This substantial variation in return predictability was also examined in Bossaerts and Hillion (1999), Lettau and Ludvigson (2001) and Welch and Goyal (2008). Sudden and sharp changes in model parameters are consistent with empirical findings in Dangl and Halling (2012) and Johannes et al. (2009), who suggest that the changes in the model return predictability parameter can be large. Like Pettenuzzo and Timmermann (2011), we identify two events that may induce large structural breaks and create contagion to be the financial crisis and the Arab Spring.

The financial crisis of 2008/2009 originated in modern financial centres (in the US precisely), as highlighted in Shalini and Prasanna (2015), but because of the integration of financial markets, its impact was amplified. As reported in Blanchard (2008) and Lin and Martin (2011), some of the primary causes of this crisis included lack of financial regulation, loose monetary policy, complex securitisation techniques and real estate burst.

Identifying the starting point as well as the end point of a crisis period is subjective. Most studies on contagion also faced similar problems in identifying the contagion event, especially for short-lived events. However, since the crisis originated from the US, I will use the VIX index to identify the contagion period. The VIX index is also popularly known as the “fear index” or the “fear gauge”. The CBOE volatility index (VIX)[28] is a measure of market expectations of near-term volatility conveyed by the S&P500 stock index option prices. I use this as a tool to identify the financial crisis contagion event in my analysis.

[28] See http://www.cboe.com/micro/vix/vixintro.aspx

Figure 3.2 CBOE market volatility index 2004–2015 [29]

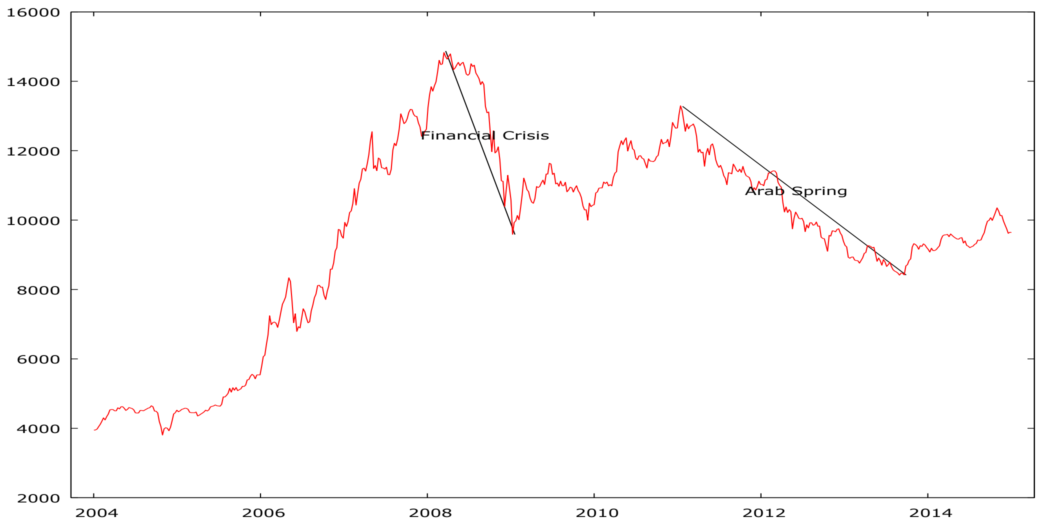


[29] Source: Reuters. Shows the series of events around the start of the financial crisis. Detailed timeline of the events within the Arab Spring and financial crisis periods are shown in appendix one of the chapter appendices.

On the other hand, the Arab Spring represents a collective wave of events that started in December 2010 with the self-immolation of Mohamed Bouazizi on 18 December 2010, in Tunisia. As stated in Hearn and Piesse (2014), this has generated an unprecedented wave of political upheaval across the Middle East and North Africa (MENA) region. Within North Africa, the Arab Spring has resulted in the popular overthrow of governments in Egypt, Libya and Tunisia, while considerable political and governmental reforms have been implemented in Morocco and, to a lesser extent, Algeria. For the purpose of the contagion variable, I define the start of the Arab Spring as 14 January 2011, with the resignation of the Tunisian president, and the end as 19 October 2012, with the death of Wissam al-Hassan,[30] a brigadier-general of the Lebanese internal security forces.

These two periods are represented in Figures 3.3, 3.4 and 3.5 for Morocco, Egypt and South Africa, respectively. The contagion from the financial crisis in the US is the bear market on the country's main stock index, while the contagion from the Arab Spring is the bear market after the 2010 event in Tunisia (described above).

Figure 3.3[31] Weekly closing prices of the Casablanca SE All Share index from 01/01/2004 to 01/01/2015, showing the bear period for the financial crisis and the Arab Spring



[30] See chapter appendices for full timeline.

[31] Data source: Reuters eikon

Figure 3.4[32] *Weekly closing prices of Egypt's EGX30 index from 01/01/2004 to 01/01/2015, showing the bear period for the financial crisis and the Arab Spring*

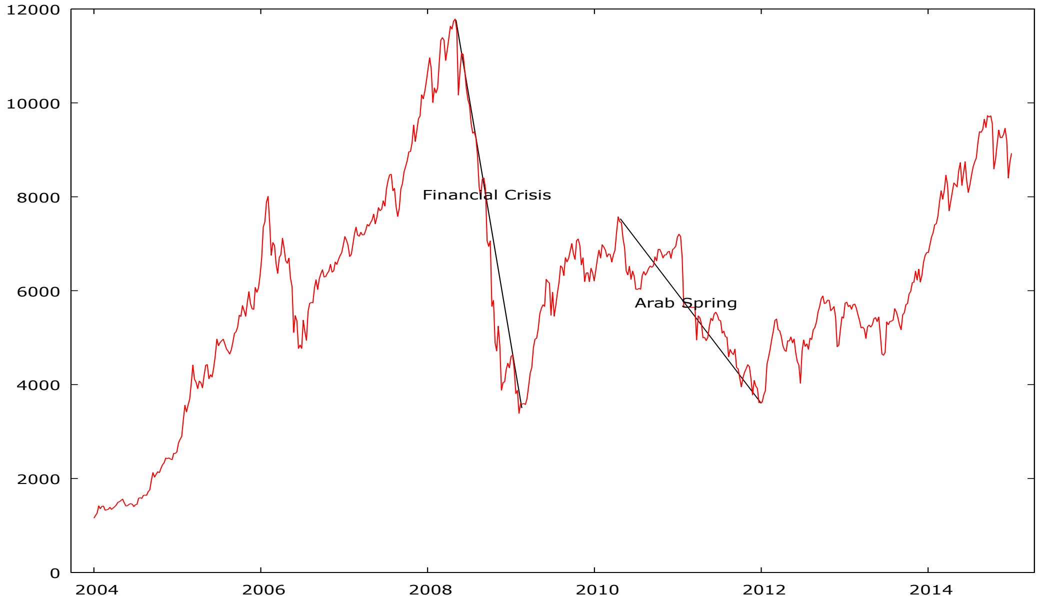
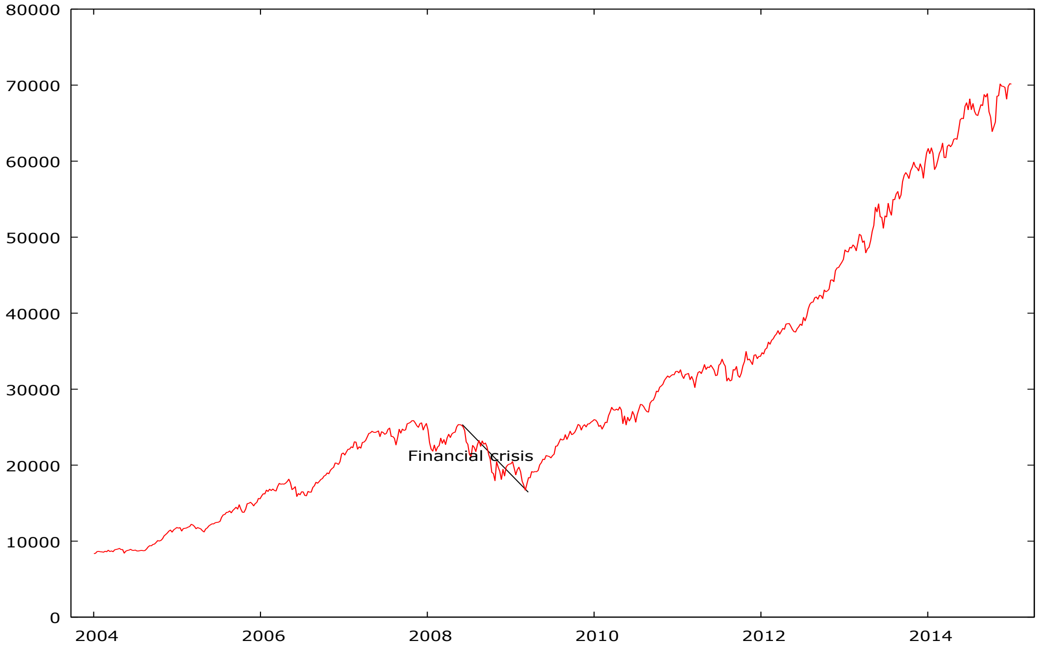


Figure 3.5[33] *Weekly closing prices of the Johannesburg Stock Exchange All Share Industrials from 01/01/2004 to 01/01/2015, showing the bear period for the financial crisis*



For an initial assessment of the impact these two events have had on the return series, I will analyse the risk-return relationship using dummy variables. The period for the financial crisis

[32] Data source: Reuters eikon
[33] Data source: Reuters eikon

to be used is from 5 September 2008 to 29 May 2009, while the period of the Arab Spring to be used is from 14 January 2011 to 19 October 2012. This is based on the most overlapping volatility period as shown in the emerging African market index (which includes Morocco and Egypt) in Section 5.4.

The effect of both the financial crisis and the Arab Spring on the African market (the other African markets, in the case of the Arab Spring), will be classified as a contagion effect; hence, in our analysis a single dummy variable will represent both events. According to Collins and Biekpe (2003), contagion is the spread of market disturbance from one market to another. However, Morales and Andreosso-O'Callaghan (2014) point out that there is no unanimously agreed definition of contagion, citing several definitions and methodologies developed in the literature. According to Dornbusch, Park and Claessens (2000), there are two separate causes of contagion; one is through a fundamental spillover resulting from the normal interdependence among economies and the second is related to fundamentals and looks to investor behaviour for an explanation.

This study does not focus on defining or measuring contagion per se, but will use the concept of contagion as a proxy for the financial crisis (which started in the US) and the Arab Spring (which started in Tunisia). For an excellent view of contagion in the African market, see Collins and Biekpe (2003) and Morales and Andreosso-O'Callaghan (2014).

Beta will also be modelled, with the impact of contagions analysed within the process of determining if beta is stable. This will be discussed in greater detail in Chapter 6.

3.7 Diagnostics

Classic autocorrelation and heteroscedasticity diagnostics will be carried out as part of the analysis. It is quite possible to eliminate or at least mitigate the problem of autocorrelation by specifying the dynamics of the model more fully, i.e. by including relevant lagged variables on a time-series model. Autocorrelation tests are carried out using Cochrane-Orcutt, Hildreth-Lu and Prais-Winsten in Gretl. Tests for heteroscedasticity were carried out using White's test, Breusch-Pagan tests (See Greene, 2003) and Keonker tests.

Where one or more of the tests indicated that autocorrelation and/or heteroscedasticity is present in the form of an unknown function of the regressors that can be approximated by a quadratic relationship, a heteroscedasticity/autocorrelation-corrected model or a heteroscedasticity-corrected model within Gretl is applied. The description within Gretl indicates that "this offers the possibility of consistent standard errors and more efficient parameter estimates as compared with OLS. The procedure involves (a) OLS estimation of the model of interest, followed by (b) an auxiliary regression to generate an estimate of the error variance, then finally (c) weighted least squares, using the reciprocal of the estimated variance as weight."

In the auxiliary regression (b) I regress the log of the squared residuals from the first OLS on the original regressors and their squares. The log transformation is performed to ensure that the estimated variances are non-negative. I call the fitted values from this regression u*. The weight series for the final WLS is then formed as 1/exp(u*).

A correlogram is further used for autocorrelation tests. As stated within the Gretl software, the correlogram to be used prints the values of the autocorrelation function for series, which may be specified by name or number. The values are defined as $\rho(u_t, u_{t-s})$, where u_t is the t^{th} observation of the variable u and s denotes the number of lags.

The partial autocorrelations (calculated using the Durbin–Levinson algorithm) are also shown; these are net of the effects of intervening lags. In addition, the Ljung–Box Q-statistic is printed. This may be used to test the null hypothesis that the series is "white noise"; it is asymptotically distributed as chi-square, with degrees of freedom equal to the number of lags used.

If an order value is specified, the length of the correlogram is limited to at most that number of lags, otherwise the length is determined automatically, as a function of the frequency of the data and the number of observations.

3.8 Methodological review and empirical models

3.8.1 Introduction

In analysing the distribution characteristics of emerging market returns, Bekaert et al. (1998) found that emerging equity markets have high volatility, low correlation with developed markets and, within the emerging markets, high long-horizontal returns and predictability above and beyond what is found in developed market returns. These have been found to be even more severe in the African market. They also indicate that the efficient frontier is pushed forward when emerging market returns are plugged into the standard Markowitz (1959) framework and even further with the inclusion of African market returns. This is because of a combination of low correlation and high expected return. I conclude that because African market returns cannot be completely characterised by the traditional mean-variance measures of the CAPM, application in these markets becomes problematic.

Given the sample and the data problems highlighted and corrected for above, this chapter will analyse the alternative methodological issues relating to the research questions identified in Chapter 2 (literature review) – i.e. relating to the gaps in the literature. These gaps relate to the effects of liquidity on asset pricing in the African market, the role of conditional information in determining excess returns in the African market, the explanatory power of higher-order moments in the African market and the effect of survivorship bias on asset-pricing models in the African market.

3.8.2 Multifactor models and the liquidity factor

According to Levy (2010), the Sharpe-Lintner CAPM is still alive and well, despite the criticisms against it. Hence it will be a good starting point for investigating the important risk factors in the African market.

The Sharpe-Lintner CAPM is denoted as

$$E(R_i) - R_f = [E(R_M) - R_f)]\beta_{iM}, i = 1, \ldots, N. \ (3.1)$$

According to the literature review (Sections 2.3 and 2.4), I expect differences between the developed and the African markets, as the literature suggests that African market returns may not be completely characterised by the traditional Sharpe-Lintner CAPM. Hence, the performance of the Fama and French (1992, 1996) model in explaining returns in the African market, as well as other multifactor models, will also be investigated. The Fama and French three-factor CAPM model is denoted as:

$$E(R_{it}) - R_{ft} = \beta_{iM}[E(R_{Mt}) - R_{ft}] + \beta_{is}E(SMB_t) + \beta_{ih}E(HML_t) \ (3.2)$$

The Carhart (1997) model is also analysed as there are tendencies for behavioural biases to be present in markets that are not fully developed, as seen in Section 2.2.6 of Chapter 2. Carhart (1997) includes momentum as measured in Jegadeesh and Titman (1993) in the Fama-French three-factor model as:

$$E(R_{it}) - R_{ft} = \beta_{iM}\left[E(R_{Mt}) - R_{ft}\right] + \beta_{is}E(SMB_t) + \beta_{ih}E(HML_t) + \beta_{im}E(UMD_t) \quad (3.3)$$

Where $E(R_{it}) - R_{ft}$ is the expected return on a portfolio in excess of the risk-free rate, $R_{Mt} - R_{ft}$ is the excess return on a broad market portfolio, SMB_t (small minus big) is the difference between the return on diversified portfolio of small stocks and that of large stocks, HML_t (high minus low) is the difference in return of a diversified portfolio of high and low book-to-market stocks, while UMD_t (up minus down) is the difference between the return on diversified portfolio of winner stocks and loser stocks. $E(R_{Mt}) - R_{ft}$, $E(SMB_t)$, $E(HML_t)$ and $E(HML_t)$ are expected premiums and the betas are slopes in the time-series regression.

However, within the African market Hearn and Piesse (2009) (and as also seen in Chapter 2, Section 2.4) specify the importance of including a measure of liquidity within the pricing model. They explain that significant bias in the beta is added through low variances and covariance between series, created through a high degree of price rigidity resulting from the presence of severe illiquidity problems in these markets. Bakaert et al. (2003) reveal that models that take liquidity into account outperform other models that incorporate only market risk factors in predicting returns.

Following Hearn and Piesse (2009), a liquidity factor will augment the Carhart four-factor model, where the liquidity factor will account for the difference in return of a diversified portfolio of high illiquid stocks and very liquid stocks, (illiquid minus very liquid).

The models are extended to test for the importance of liquidity by the IMV factor in a time-series regression in a five-factor model. The five-factor model will be constructed using Carhart's (1997) four-factor model and the additional factor capturing liquidity. This five-factor model is consistent with a model of market equilibrium with five risk factors. Hence, performance will be estimated relative to the five-factor models as:

$$E(R_{it}) - R_{ft} = \beta_{iM}\left[E(R_{Mt}) - R_{ft}\right] + \beta_{is}E(SMB_t) + \beta_{ih}E(HML_t) + \beta_{im}E(UMD_t) + \beta_{ip}E(IMV_t) \quad (3.4)$$

where $E(R_{Mt}) - R_{ft}$, $E(SMB_t)$, $E(HML_t)$, $E(UMD_t)$, $E(IMV_t)$ are expected premiums and the factor sensitivities or loading, β_{iM}, β_{is}, β_{ih}, β_{im} and β_{ip}, are the slopes in the time-series regression, ε_{it} is a random shock distributed IN(0,σ_i^2)

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \beta_{is} SMB_t + \beta_{ih} HML_t + \beta_{im} UMD_t + \beta_{ip} IMV_t + \varepsilon_{it} \quad (3.5)$$

However, as highlighted in Lesmond (2005), it is quite difficult to define liquidity, let alone estimate it. The measures of liquidity available in the literature include those of Roll (1984), Lesmond et al. (1999), Amihud (2002), Jain (2002) and Lesmond (2005).

Broadly, the measures of liquidity are dependent on firstly trading costs that are based on bid-ask quotes. However, due to the frequent deviation of closing prices from the quotes resulting from consummation of trades at different pricing and sometimes at prices outside the quotes, these quotes are not always available for all time periods in all markets. This lack of information has led to the second class of estimators based on volume, specifically turnover and Amihud's measure, in Amihud (2002).

However, some problems arise with the use of turnover as it fails to account for cost per trade and also turnover is likely to increase during periods of credit crises when liquidity decreases, rather than decreasing to reflect this liquidity decease within the market, as Lesmond (2005) points out. The last liquidity estimators require only price information instead of volume information. This includes the estimators in Roll (1984), who uses an estimator of implied effective spread based on measuring the negative autocorrelation produced by bounces between the bid and ask quotes. Lesmond (2005) explains that this estimator should be positively related to the bid-ask spread. However, they highlight that sometimes the serial autocorrelation is positive, thereby invalidating the estimate.

The liquidity measure includes the bid-ask spread liquidity measure of Lesmond (2005), which is shown as:

$$Quoted\ spread_M = \frac{1}{2}\left[\left(\frac{(Ask_M - Bid_M)}{(Ask_{\ M} + Bid_M)/2}\right) + \left(\frac{(Ask_{M-1} - Bid_{M-1})}{(Ask_{M-1} + Bid_{M-1})/2}\right)\right] \quad (3.6)$$

Bid-ask spreads that exceed 80% are trimmed, as these are potentially coding errors.

The turnover measure of liquidity is shown in Liu (2006), where the liquidity measure of a security, LM_x, is defined as the standardised, turnover-adjusted number of zero daily trading volume over the prior x months ($x = 1$, 6, 12), represented as:

$$LM_x = \left[(Number\ of\ zero\ daily\ volumes\ in\ prior\ \times months)\ + \frac{\frac{1}{x}month\ turnover}{Deflector}\right] \times \frac{21x}{NoTD}\ (3.7)$$

where $x$month turnover is the turnover over the prior x months. $NoTD$ is the total number of trading days over the prior x months and deflector is chosen such that

$$0 < \frac{1/(x\ month\ turnover)}{Deflector} < 1\ (3.8)$$

for all stocks. Due to variations in trading days, typically from 15 to 23 days per month, 21x/NoTD standardises the number of monthly trading days to 21, making the liquidity measure comparable over time. $LM1$ is the turnover-adjusted number of zero daily trading volume over the prior 21 trading days, with 1 reflecting the period of measurement. Equation (3.8) captures multiple dimensions of liquidity, placing considerable emphasis on trading speed, which up until now has been largely ignored in the literature. According to Liu (2006), this liquidity measure also reflects the bid-ask spread measure documented in Lesmond et al. (1999). A detailed step in estimating this measure is reported in Liu (2006).

Amihud's measure defines stock illiquidity as:

$$Q_{ix} = 1/D_{ix} \sum_{t=1}^{D_{ix}} |R_{ixd}|/V_{ixd}, \qquad (3.9)$$

where D_{ix} is the number of days for which data are available for stock i in year x, $|R_{ixd}|/V_{ixd}$ is the (dollar) trading volume on day d, R_{ixd} is the return on stock i on day d of year x and V_{ixd} is the daily volume in dollars respectively. As stated in Amihud (2002), the measure follows the concept of illiquidity in Kyle (1985) and the thinness measure in Silber (1975).

As stated in Lesmond (2005), the most demonstrable indicator of overall liquidity still remains the bid-ask quote. Given that the bid-ask quotes required are available, this study will employ the bid-ask spread estimate for liquidity.

3.8.3 Higher-order moments

In their review of the robust measures of skewness and kurtosis, Kim and White (2004) highlight the following; assuming that y_ts are independent and identically disturbed with a cumulative distribution function F, in the process $\{y_t\}_{t=1,2,\dots,N}$ the coefficients of skewness and kurtosis (in its conventional form) for $y_t$are given by:

$$SK_1 = E\left(\frac{y_t - \mu}{\sigma}\right)^3, (3.10)$$

$$KR_1 = E\left(\frac{y_t - \mu}{\sigma}\right)^4 - 3, (3.11)$$

where $\sigma^2 = E(y_t - \mu)^2$ and $\mu = E(y_t)$, and expectation E is taken with respect to F. Given data $\{y_t\}_{t=1,2,\dots,N}$, SK_1 and KR_1 are usually estimated by the sample averages:

$$\widehat{SK}_1 = T^{-1}\sum_{t=1}^{N}\left(\frac{y_t - \hat{\mu}}{\hat{\sigma}}\right)^3, (3.12)$$

$$\widehat{KR}_1 = T^{-1}\sum_{t=1}^{N}\left(\frac{y_t - \hat{\mu}}{\hat{\mu}}\right)^4 - 3\ (3.13)$$

where $\hat{\sigma}^2 = T^{-1}\sum_{t=1}^{N}(y_t - \hat{\mu})^2, \hat{\mu} = T^{-1}\sum_{t=1}^{N} y_t$.

Using the GMM model estimator and a multivariate approach, and focusing on emerging markets, Hwang and Satchell (1999) proposed the use of the four-moment CAPM over the conventional mean-variance CAPM. This, they say, results from non-stationarity in emerging markets, due to the evolving degree of market integration, re-emerging and survivorship bias in data, bias related to the selection of country, significant non-economic factors such as political factors and the evolution from an emerging to a mature market. Chiao, Hung and Srivastava (2003) support this view and report that when the distribution of returns has a positive coskewness, investors expect a lower return. On the other hand, when it has a positive cokurtosis, they expect a higher return. They also show the importance of relative coskewness and cokurtosis risks over covariance risks in regards to return variation, insisting that this is particularly evident in the bull market subperiod.

Other authors who have investigated the limitations of the mean-variance approach include Arditti (1971), Jean (1971, 1973) and Arditti and Levy (1975), who explored the relationship between skewness and return of individual securities and portfolios, and Friend and Westerfield (1980), Simkowitz and Beedles (1978), Sears and Wei (1985), Barone-Adesi (1985), Chunhachinda et al. (1997), Lim (1989), Tan (1991) and Harvey and Siddique (1999, 2000), who investigated the importance of skewness in asset pricing. While Fama (1963) inferred that stock returns have fat tails, Sears and Wei (1988) insisted that ignoring the coskewness risk may bias estimates in risk-return trade-off tests. Fang and Lai (1997) find that investors are rewarded with higher expected returns for bearing systematic cokurtosis, covariance and coskewness risks.

An even more interesting assessment has surfaced with Kim and White (2004) asking: "How useful are the conventional measures of skewness and kurtosis used in asset-pricing models?" This question, they insist, results from the use of averages, which are not robust, in the computation of skewness and kurtosis. They insist that in the presence of one or more large outliers, the values become arbitrarily large. However, they recognise that an apparently straightforward solution would be to eliminate the outliers from the data, but they maintain that removing outliers manually would be subjective and arbitrary. They thus insist on a more robust measure of skewness and kurtosis. An example of this is the use of median for location and interquartile range for dispersion (as they are quantile-based). Subsequently, a coefficient of skewness was developed by Bowley (1920) and its simplest form is represented as:

$$SK_2 = \frac{Q_3 + Q_1 - 2Q_2}{Q_3 - Q_1} \quad (3.14)$$

where $Q_1 = F^{-1}(0.25), Q_2 = F^{-1}(0.5),$ and $Q_3 = F^{-1}(0.75)$ - (as Q_i is the ith quartile of y_t). From the above, it is obvious that the Bowley coefficient of skewness is zero for any symmetric distribution. SK_2 of -1 corresponds to extreme left skewness, while SK_2 of 1 corresponds to extreme right skewness, as the denominator $Q_3 - Q_1$ rescales the coefficient.

Other modifications include the generalisation of the Bowley coefficient of skewness by Hinkley (1975) and a further modification of Hinkley's coefficient by Groeneveld and Meeden (1984).

As stated in Kim and White (2004), the conventional kurtosis KR_1 measure can be large when probability mass is concentrated either near the mean μ or in the tails of the distribution. This follows that KR_1 can be construed as a measure of a distribution dispersion around the two values $\mu \pm \sigma$. Resulting from this analysis, Moors (1988) developed a robust alternative to KR_1:

$$\frac{(E_7 - E_5) + (E_3 - E_1)}{E_6 - E_2} \quad (3.15)$$

where $E_i = F^{-1}\left({}^{i}\!/_{8}\right)$ for $i = 1,2,...,7$, as E_i is the ith octile. Other forms of this measure, which follow from Moore's centred coefficient, include those of Hogg (1974) and Crow and Siddiqui (1967).

However, the most popular measure of coskewness and cokurtosis still remains that of Kraus and Litzenberger (1976). This is largely due to the relative ease of application as seen in Chiao, Hung and Srivastava (2003). The Kraus and Litzenberger (1976) measure is:

$$S_i = \hat{\gamma}_i = \frac{\sum_{t=1}^{-80}[(R_{mt} - \bar{R}_{it})(R_{mt} - \bar{R}_{mt})^2]}{\sum_{t=1}^{-80}(R_{mt} - \bar{R}_{mt})^3} \quad (3.16)$$

$$K_i = \hat{\delta}_i = \frac{\sum_{t=1}^{-80}[(R_{mt} - \bar{R}_{it})(R_{mt} - \bar{R}_{mt})^3]}{\sum_{t=1}^{-80}(R_{mt} - \bar{R}_{mt})^4} \quad (3.17)$$

R_{it} and R_{mt} are the returns of asset i (index returns) and the market, respectively, and $\bar{R}_{it}$ and $\bar{R}_{mt}$ are the expected returns on asset i and the expected market returns, respectively. This skewness and kurtosis measure follows the measures in Kraus and Litzenberger (1976) and Barone-Adesi (1985) designed to avoid the risk of spurious correlation between the systematic risks of the portfolio.

However, as seen in Kim and White (2004) there may be an outlier problem with this measure. Hence the application of these measures can only be recommended along with a robust method of dealing with outliers. The method for dealing with the outlier problem is highlighted in Section 3.9 below.

3.8.4 CAPM with structural breaks

The stable relationship between expected return and beta has been seriously questioned in Garcia and Ghysels (1998), who argue that this relationship may not hold due to the presence of structural breaks. This will mean that I need not always reject or accept the CAPM for the whole period as the single possible result, as the structural change modelling strategy allows for different dynamic behaviour among different regimes. The structural change model to be employed in this research will mimic the models in Bai and Perron (2003) and Huang and Cheng (2003).

The following multiple linear regression will be specified to have ($m + 1$ regimes) as:

$$y_t = w_t' \cap + z_t'\delta_j + u_t, \qquad t = T_{j-1} + 1, \dots, T_j \quad (3.18)$$

for $j = 1, \dots, m + 1$. y_t is the observed dependent variable at t, w_t ($v\times1$) and z_t ($q\times1$) are vectors of the explanatory variables with corresponding coefficients $\cap$ and δ_j, ($j = 1, \dots, m + 1$), and the disturbance term u_t. The coefficient vector β is not subject to shift and is estimated using the whole sample; hence this model is that of partial structural change. A pure structural change model is obtained where all parameters subject to change when $p = 0$. The indices ($T_1, \dots, T_m$), or the break points (T_j) = $(T_1, \dots, T_m)'$ are explicitly treated as unknown (the convention $T_0 = 0$ and $T_{m+1} = T$).

To obtain our structural change CAPM, adjustments need to be made to Equation 3.18 as it is a very general setup. To make the adjustments I set $p = 0$ and redefine y_t = r_t, $z_t = (1, r_{mt})'$, and $\delta_j = (\alpha_j, \beta_j)'$, hence Equation 3.18 can be written as:

$$r_t = z_t'\delta_j + u_t \quad (3.19)$$

The purpose here is to estimate the unknown parameters α_j and β_j for $j = 1,2,..,m + 1$, and the break points based on T observations on r_t and r_{mt}. All parameters are subject to shifts resulting in a pure structural change model.

Estimation of the structural change model will follow the process detailed in Huang and Cheng (2003), following the works of Hansen (2000) and Bai and Perron (2003).

3.8.4.1 Test statistics for multiple structural changes

Three F −related test statistics for multiple breaks have been proposed by Bai and Perron (1998, 2003). A brief discussion of the test statistics is as follows.

A test of no break versus a fixed number of breaks

As stated in Bai and Perron (1998, 2003), I consider the sup F type test of no structural break ($m = 0$) against the alternative hypothesis of $m = k$ breaks. Let $(T_1, \dots, T_k)$ be a partition such that $T_i = [T\lambda_i]$ and $i = 1, \dots, k$. Let R be the conventional matrix such $(R\delta)' = (\delta_1' - \delta_2', \dots, \delta_k' - \delta_{k+1}')'$

Define:

$$F_T^*(\lambda_1, \dots, \lambda_k; q) = \frac{1}{T}\left(\frac{T - (K+1)q - p}{kq}\right)\hat{\delta}' R' \left(R\hat{V}\left(\hat{\delta}\right)R'\right)^{-1} R\hat{\delta}, \quad (3.20)$$

where $\hat{V}\left(\hat{\delta}\right)$ is an estimate of the variance covariance matrix of $\hat{\delta}$ that is robust to serial correlation and heteroscedasticity; i.e., a constant estimate of:

$$V\left(\hat{\delta}\right) = \text{plim} T(\bar{Z}'\bar{Z})^{-1}\bar{Z}'\Omega\bar{Z}(\bar{Z}'\bar{Z})^{-1} \quad (3.21)$$

F_T^* is just the conventional F-statistic for testing $\delta_1 = \cdots = \delta_{k+1}$ against $\delta_1 \neq \delta_{i+1}$ for some i given the partition $(T_1, \dots, T_K)$. The test is:

$$supF_T(k; q) = F_T\left(\hat{\lambda}_1, \dots, \hat{\lambda}_k; q\right) \quad (3.22)$$

where $(\hat{\lambda}_1, \dots, \hat{\lambda}_k)$ minimises the global effect of squared residuals under the specified trimming. This is much simpler to construct, while still being asymptotically equivalent to maximising the F test in Equation 3.20. This is because even in the presence of serial correlation, the estimated break dates are still consistent.

Double maximum tests

Bai and Perron (1998) introduced the double maximum test, which is made up of two tests of null hypothesis of no structural break against an unknown number of breaks giving some upper bound M. The first test is an equal-weighted version as follows:

$$UDmaxF_T(M,q) = \max_{1 \le m \le M} F_T(\hat{\lambda}_1, \dots, \hat{\lambda}_k; q) \quad (3.23)$$

The second test applies weights to the individual tests such that the marginal p values are equal across values of m and is denoted as:

$$WDmaxF_T(M,q) = \max_{1 \le m \le M} \frac{c(q,\alpha,1)}{c(q,\alpha,m)} F_T(\hat{\lambda}_1, \dots, \hat{\lambda}_k; q) \quad (3.24)$$

where $c(q,\alpha,m)$ represents the asymptotic critical value of the test $F_T(\hat{\lambda}_1, \dots, \hat{\lambda}_k; q)$. $WDmaxF_T(M,q)$ depends on the significance level chosen since the weights themselves depend on α. The weights are defined as $a_1 = 1$ and $a_m = c(q,\alpha,1)/c(q,\alpha,m)$.

A test of ℓ versus $\ell + 1$ breaks.

As an alternative, Bai and Perron (1998) introduced a test for ℓ versus $\ell + 1$ breaks, denoted as $sup\, F_T\ (\ell + 1|\ell)$. The method amounts to the application of $(\ell + 1)$ tests of the null hypothesis of no structural change. The test apples to each segment containing the observations $\hat{T}_{i-1}$ to $\hat{T}_i$ for $i = 1, \dots, \ell + 1$ where $\hat{T}_0 = 0$ and $\hat{T}_{\ell+1} = T$. They conclude that a rejection in favour of a model with $(\ell + 1)$ breaks, if the overall minimal value of the sum of squared residuals is significantly smaller than the sum of residuals from the ℓ break model. The break date thus selected is the one associated with this overall maximum.

In conclusion, Bai and Perron (2003) document that a useful strategy is to carry out the *WD* max or *UD* max test to investigate the presence of at least one break. If a break exists following these tests, a sequential examination of the sup$F(l + 1 \mid l)$ statistics constructed using global minimisers for the break dates can be used to decide the number of breaks.

3.8.4.2 Results of structural break tests

I follow the methods identified above to perform structural break tests on the market indices within the emerging and frontier African market countries. This method is essential as it allows us to identify shifts in volatility endogenously in contrast to methods where regime shifts are imposed on *a priori* grounds. The structural break tests are important given the criticisms and issues associated with the unconditional CAPM as identified in Section 2.5 in Chapter 2. As identified earlier, there are two events that I expect will lead to regime shift in the return-generating process; however, there may also be some unexpected breaks that do not seem obvious when I observe the time-series plots of the data. I therefore develop two hypotheses to account for all breaks.

Hypothesis 1

There is ***NO*** structural break in the market indices of the emerging African markets.

Hypothesis 2

There is ***NO*** structural break in the market indices of the frontier African markets.

The structural break methodology adopted in this section is the Bai-Perron test as examined earlier. I test the stability of the market indices in the emerging African market (South Africa, Egypt and Morocco) and the frontier African market (Botswana, BRVM in Cote d'Ivoire, Kenya, Nigeria and Tunisia). I apply Equation 3.22 and the double maximum tests (unweighted max-F (*UDmax*) and weighted max-F (*WDmax*), as in Equation 3.23 and 3.24. I specify the maximum number of breaks as five, with trimming of 0.15. The test statistics employ HAC covariances (quadratic-spectral kernel, Andrews bandwidth) and allow heterogeneous error distribution across breaks. The results for the tests are shown below.

Emerging African market

Table 3.13 Result for the test of no break versus a fixed number of breaks for the South African market index[34]

Estimated number of breaks	5
Maximum number of breaks	5
Breaks	26/8/2005, 20/4/2007, 29/1/2010, 23/9/2011, 17/5/2013

The following events occurred around the break dates:

26/8/2005 – Week after strike action by the South African Municipal Workers Union over wage dispute.
20/4/2007 – The JSE TradElect system (electronic trading) replaced the JSE SETS system.
29/1/2010 – South Africa officially submitted its targets to reduce emissions by 34% by 2020 and 42% by 2025 to the Copenhagen Accord.[35]
23/9/2011 – Statement from the monetary policy committee of the South African reserve bank highlighting a significant increase in downside risks to the global and domestic growth prospects.[36]
17/5/2013 – Figures were released on the growth of the economy, indicating that the economy slowed sharply in the first three months of the year when compared to the previous quarter.[37]

[34] Result output is shown in chapter appendix A3.2a and the actual, fitted and residual graph is shown in chapter appendix A3.2b
[35] http://www.ieta.org/resources/Resources/Case_Studies_Worlds_Carbon_Markets/south_africa_case_study_may2015.pdf
[36] https://www.resbank.co.za/Lists/News%20and%20Publications/Attachments/4899/01Full%20Quarterly%20Bulletin.pdf
[37] http://www.bbc.co.uk/news/business-22690531

Table 3.14 Result for the test of no break versus a fixed number of breaks for the Egyptian market index[38]

Estimated number of breaks	3
Maximum number of breaks	5
Breaks	19/8/2005, 6/4/2007, 21/11/2008

The following events occurred around the break dates:

19/8/2005 – Week following a series of terrorist attacks in the Egyptian resort city of Sharm el-Sheikh.
6/4/2007 – This followed continued improvement in the Egyptian economy, highlighted by the addition of 2.4 million jobs as at the end of March 2007, from the end of 2004. This also followed strong levels of FDI and rising equity and real estate prices, leading to a peak in CPI of 12.8% in 2007.[39]
21/11/2008 – This relates to contagion from the financial crisis.

Table 3.15 Result for the test of no break versus a fixed number of breaks for the Moroccan market index[40]

Estimated number of breaks	4
Maximum number of breaks	5
Breaks	26/8/2005, 20/4/2007, 12/12/2008, 13/4/2012

The following events occurred around the break dates:

26/8/2005 – Western Sahara's exiled Polisario Front independence movement has released all of its remaining Moroccan prisoners of war, a total of 404.[41]
20/4/2007 – This followed a series of bombings in Casablanca on 11 March, 10 April and 14 April.
12/12/2008 – The financial crisis period.
13/4/2012 – Morocco aids drought-stricken farmers.[42]
17/11/2006 – Hotel shortage threatens Morocco's tourism industry.

Frontier African market

Table 3.16 Result for the test of no break versus a fixed number of breaks for the Botswanan market index[43]

Estimated number of breaks	5
Maximum number of breaks	5
Breaks	26/8/2005, 20/4/2007, 12/12/2008, 22/7/2011, 22/3/2013

The following events occurred around the break dates:

26/8/2005 – Worries about high inventories cast a shadow over the main diamond markets, as traders worried about the potential impact on polished prices.[44]

[38] Result output is shown in chapter appendix A3.4a and the actual, fitted and residual graph is shown in chapter appendix A3.4b
[39] https://www.imf.org/external/np/ms/2007/091207.htm
[40] Result output is shown in chapter appendix A3.6a and the actual, fitted and residual graph is shown in chapter appendix A3.6b
[41] http://edition.cnn.com/2005/WORLD/europe/08/18/morocco.release/
[42] http://www.moroccoworldnews.com/2012/04/34981/morocco-aids-drought-stricken-farmers/
[43] Result output is shown in chapter appendix A3.8a and the actual, fitted and residual graph is shown in chapter appendix A3.8b
[44] https://www.polishedprices.com/go/market-news/weekly-market-reports~3165

20/4/2007 – The methodology for calculating the market indices was changed from a simple market-cap weighted calculation to a volume-adjusted market cap as a result of a new upward trend.[45]
12/12/2008 – Drop in the operation of the personal transport section index, which was attributed to the fall in retail prices of both diesel and petrol by P1.0 per litre.[46]
22/7/2011– Botswana to ban wildlife hunting, which could affect tourism.[47]
22/3/2013 – Poor economic data announced.

Table 3.17 Result for the test of no break versus a fixed number of breaks for the BRVM - Cote d'Ivoire market index[48]

Estimated number of breaks	2
Maximum number of breaks	5
Breaks	13/1/2006, 17/5/2013

The following events occurred around the break dates:

13/1/2006 – Ivory Coast toxic waste dump.
17/5/2013 – A pledge by the Ivorian government to pursue a 10-year poultry farming revitalisation.[49]

Table 3.18 Result for the test of no break versus a fixed number of breaks for the Kenyan market index[50]

Estimated number of breaks	3
Maximum number of breaks	5
Breaks	16/1/2009, 29/1/2010, 29/3/2013

The following events occurred around the break dates:

16/1/2009 – Poor harvest in Kenya.[51]
29/1/2010 – Kenya to improve the handicraft sector.[52]
29/3/2013 – Kenyatta wins the presidential election.[53]

Table 3.19 Result for the test of no break versus a fixed number of breaks for the Nigerian market index[54]

Estimated number of breaks	5
Maximum number of breaks	5
Breaks	26/8/2005, 20/4/2007, 12/12/2008, 27/5/2011, 8/1/2013

The following events occurred around the break dates:

[45] http://allafrica.com/stories/200708070873.html
[46] http://www.sundaystandard.info/december-inflation-falls-line-expectation

[47] http://goodnature.nathab.com/botswana-to-ban-wildlife-hunting/
[48] Result output is shown in chapter appendix A3.10a and the actual, fitted and residual graph is shown in chapter appendix A3.10b
[49] http://www.ghanaweb.com/GhanaHomePage/NewsArchive/Injaro-invests-in-C-te-d-Ivoire-poultry-sector-274284
[50] Result output is shown in chapter appendix A3.12a and the actual, fitted and residual graph is shown in chapter appendix A3.12b
[51] http://earthobservatory.nasa.gov/NaturalHazards/view.php?id=36683
[52] http://www.capitalfm.co.ke/business/2010/01/kenya-to-revamp-handicraft-sector/
[53] http://www.ft.com/cms/8c6320a8-7c4b-11e2-99f0-00144feabdc0.html?ft_site=falcon&desktop=true
[54] Result output is shown in chapter appendix A3.14a and the actual, fitted and residual graph is shown in chapter appendix A3.14b

26/8/2005 – Oil bid round records largest turnout of players.[55]
20/4/2007 – Disputed general elections held[56]
12/12/2008 – Supreme Court upheld the results of the presidential election[57]
27/5/2011 – Presidential elections held[58]
18/1/2013 – Nigerian economy estimated to grow at 6.8%[59]

Table 3.20 Result for the test of no break versus a fixed number of breaks for the Tunisian market index [60]

Estimated number of breaks	5
Maximum number of breaks	5
Breaks	21/4/2006, 1/2/2008, 18/9/2009, 23/9/2011, 10/5/2013

The following events occurred around the break dates:

21/4/2006 – Canadex's Tunisian Oil test well reached total depth[61]
1/2/2008 – Ranked 32nd for competitiveness for 2007-2008 by the World Economic Forum[62]
18/9/2009 – Election in an atmosphere of repression[63]
23/9/2011 – Lead-up to parliamentary elections[64]
10/5/2013 – Poll numbers showed as significant in the political landscape, with Nidaa being more popular than Ennahda.[65]

I apply the test of **ℓ versus $\ell + 1$ breaks** as identified in Section 3.8.4.1. I use a sequential evaluation method and specify the maximum number of breaks as five with trimming of 0.15. Test statistics employ HAC covariances (Quadratic-Spectral Kernel, Andrews bandwidth) and allow heterogeneous error distribution across breaks.

Emerging African market

Table 3.21 Result for a test of ℓ versus $\ell + 1$ breaks for the South African market index [66]

Estimated number of breaks	3
Maximum number of breaks	5
Breaks	22/9/2006, 1/10/2010, 4/1/2013

55 http://www.nnpcgroup.com/PublicRelations/NNPCinthenews/tabid/92/articleType/ArticleView/articleId/230/2005-Oil-Bid-Round-Records-Largest-Turnout-Of-Players.aspx
56 http://www.npr.org/templates/story/story.php?storyId=9766502
57 http://www.state.gov/outofdate/bgn/nigeria/200317.htm

58 http://www.usip.org/sites/default/files/PB%20103.pdf
59 http://www.bloomberg.com/news/articles/2013-02-18/nigerian-economy-to-grow-6-8-in-2013-inflation-to-average-9-8-
60 Result output is shown in chapter appendix A3.16a and the actual, fitted and residual graph is shown in chapter appendix A3.16b
61 http://www.oilandgasinternational.com/html/login.aspx?ReturnUrl=%2fdepartments%2fexploration_discoveries%2fapr06_candax2.aspx
62 http://www.nomarmiteintunisia.co.uk/december2007.htm
63 https://www.hrw.org/news/2009/10/23/tunisia-elections-atmosphere-repression
64 http://www.bbc.co.uk/news/world-africa-14107720
65 http://www.al-monitor.com/pulse/politics/2013/05/tunisian-poll-ennahda-popularity-declines-nidaa-tunis.html
66 Result output is shown in chapter appendix A3.3a and the actual, fitted and residual graph is shown in chapter appendix A3.3b

The following occurred around the break dates:

22/9/2006 – A Sasol Tigers Aero L-29 Delfin crashed into Table Bay during a validation flight for the Africa Aerospace and defence air show.
1/10/2010 – South Africa's reserve bank's monetary policy committee (MPC) reduced the repurchase rate to 6%, with banks' prime overdraft rate at 9.5%, the lowest in three decades.[67]
4/1/2013 –The week before the downgrade of South Africa's long-term foreign currency issuer Default Rating from BBB+ to BBB and long-term local currency IDR from A to BBB+ by Fitch Group.

Table 3.22 Result for a test of ℓ versus $\ell + 1$ breaks for the Egyptian market index[68]

Estimated number of breaks	1
Maximum number of breaks	5
Breaks	19/8/2005

The following event occurred around the break date:

19/8/2005 –Week following a series of terrorist attacks in the Egyptian resort city of Sharm el-Sheikh.

Table 3.23 Result for a test of ℓ versus $\ell + 1$ breaks for the Moroccan market index.[69]

Estimated number of breaks	2
Maximum number of breaks	5
Breaks	17/11/2006, 6/4/2012

The following events occurred around the break date:

17/11/2006 – Hotel shortage threatens Morocco's tourism industry
6/4/2012 – "Turnover reached MAD 834.4m (USD 98.7m), significantly more than last week's MAD 441.4m and the six-month average of MAD 689.5m. The MORALSI is now -3.4% weaker for the year (-2.3% in USD terms) with total market capitalisation at USD 58.4bn."[70]

Frontier African market

Table 3.24 Result for a test of ℓ versus $\ell + 1$ breaks for the Botswanan market index[71]

Estimated number of breaks	3
Maximum number of breaks	5
Breaks	13/10/2006, 12/12/2008, 15/3/2013

The following events occurred around the break date:

13/10/2006 – Improvements in the diamonds and torsion sectors.
12/12/2008 – Drop in the operation of personal transport section index, which was attributed to the fall in retail prices of both diesel and petrol by P1.0 per litre.[72]
15/3/2013 - Poor economic data announced.

[67] http://www.gov.za/remarks-release-2010-annual-economic-report-and-september-2010-quarterly-bulletin-south-african
[68] Result output is shown in chapter appendix A3.5a and the actual, fitted and residual graph is shown in chapter appendix A3.5b
[69] Result output is shown in chapter appendix A3.7a and the actual, fitted and residual graph is shown in chapter appendix A3.7b
[70] http://www.afribiz.info/content/2012/morocco-stock-market-commentary-week-ending-april-6-2012/
[71] Result output is shown in chapter appendix A3.9a and the actual, fitted and residual graph is shown in chapter appendix A3.9b
[72] http://www.sundaystandard.info/december-inflation-falls-line-expectation

Table 3.25 Result for a test of ℓ versus $\ell + 1$ breaks for the BRVM market index. [73]

Estimated number of breaks	5
Maximum number of breaks	5
Breaks	2/12/2005, 20/7/2007, 6/3/2009, 22/10/2010, 1/3/2013

The following events occurred around the break date:

2/12/2005 – Anti-money laundering bill passed into law.[74]
20/7/2007 – Initiation of the emergency post-conflict assistance project[75]
6/3/2009 – 3.8% increase in GDP
22/10/2010 – First round of the violent elections in Ivory Coast.
1/3/2013 - Announced local elections set for 21 April; opposition Ivorian Popular Front on 15 Feb said party will boycott polls.[76]

Table 3.26 Result for a test of ℓ versus $\ell + 1$ breaks for the Kenyan market index.[77]

Estimated number of breaks	3
Maximum number of breaks	5
Breaks	16/1/2009, 29/1/2010, 29/3/2013

The following events occurred around the break date:

16/1/2009 – Poor harvest in Kenya.[78]
29/1/2010 – Kenya to improve the handicraft sector.[79]
29/3/2013 - Kenyatta wins the presidential election.[80]

Table 3.27 Result for a test of ℓ versus $\ell + 1$ breaks for the Nigerian market index[81]

Estimated number of breaks	3
Maximum number of breaks	5
Breaks	9/2/2007, 31/10/2008, 25/1/2013

The following events occurred around the break date:

9/2/2007 – Anambra state governor handed over following court verdict
31/10/2008 – Central Bank Governor gave a speech on the financial crisis[82]
25/1/2013 – Nigerian economy estimated to grow at 6.8%[83]

Table 3.28 Result for a test of ℓ versus $\ell + 1$ breaks for the Tunisian market index[84]

Estimated number of breaks	2
Maximum number of breaks	5
Breaks	27/10/2006, 4/9/2009

The following events occurred around the break date:

[73] Result output is shown in chapter appendix A3.11a and the actual, fitted and residual graph is shown in chapter appendix A3.11b
[74] http://www.anti-moneylaundering.org/africa/Ivory_Coast.aspx
[75] http://www.worldbank.org/projects/P082817/emergency-post-conflict-assistance-project?lang=en&tab=overview
[76] http://www.crisisgroup.org/en/publication-type/crisiswatch/crisiswatch-database.aspx?CountryIDs=%7BACB2D1F7-8CB1-432E-ABFB-76436AE72921%7D
[77] Result output is shown in chapter appendix A3.13a and the actual, fitted and residual graph is shown in chapter appendix A3.13b
[78] http://earthobservatory.nasa.gov/NaturalHazards/view.php?id=36683
[79] http://www.capitalfm.co.ke/business/2010/01/kenya-to-revamp-handicraft-sector/
[80] http://www.ft.com/cms/8c6320a8-7c4b-11e2-99f0-00144feabdc0.html?ft_site=falcon&desktop=true
[81] Result output is shown in chapter appendix A3.15a and the actual, fitted and residual graph is shown in chapter appendix A3.15b
[82] http://www.cenbank.org/documents/speeches.asp?beginrec=41&endrec=60
[83] http://www.bloomberg.com/news/articles/2013-02-18/nigerian-economy-to-grow-6-8-in-2013-inflation-to-average-9-8-
[84] Result output is shown in chapter appendix A3.17a and the actual, fitted and residual graph is shown in chapter appendix A3.17b

27/10/2006 – Tunisia signed the United Nations convention against corruption[85]
4/9/2009 – Election in an atmosphere of repression[86]

I reject the null hypothesis of no structural break, as each one of the series identified had at least one break based on both the test of *no break versus a fixed number of breaks* and the test *of* ℓ *versus* $\ell + 1$ *breaks.* I also observe that the breaks identified vary between the indices and even between the methods used. In the emerging African market, the test of *no break versus a fixed number of breaks* identified more break points than the test of ℓ *versus* $\ell + 1$ *breaks*. This is similar in the finding in the frontier African market except for the Cote d'Ivoire (BRVM) market index, where the number of breaks for the test of *no break versus a fixed number of breaks* is two, while the test *of* ℓ *versus* $\ell + 1$ *breaks* identified five breaks. Overall, this shows a potential for the emerging and frontier African indices formed to have significant structural changes.

The timing of the breaks indicates that volatility in the African markets differs considerably and appears to reflect country-specific developments. The breaks within these markets are also more frequent than one would expect when compared to the developed markets, as noted in McMillan and Thupayagale (2011). This is obviously due to the relative newness of these markets and problems of illiquidity and thin trading, and as a consequence are potentially more volatile than equity markets in industrialised economies. The frequent regime changes have also been reported in McMillan and Thupayagale (2011) within the African market. This does, however, increase the case for the incorporation of breaks in the unconditional variance at the very least, as identified in McMillan and Thupayagale (2011).

This indication of the instability of the structure of the series will put in doubt the assumption of constant beta in the unconditional CAPM. This is supported by Jagannathan and Wang (1996), who insist on a time-varying relative risk due to cash flow variations resulting from business cycles and the degree of a firm's financial leverage.

The Chow tests for parameter stability are further carried out on the index returns of the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market. These are done using two break points: the start of the 2008 financial crisis (5/9/2008) and the start of the Arab Spring (14/1/2011). I also employ

[85] https://www.unodc.org/unodc/en/treaties/CAC/signatories.html
[86] https://www.hrw.org/news/2009/10/23/tunisia-elections-atmosphere-repression

CUSUM tests[87] (following Brown, Durbin and Evans, 1975) and the CUSUM of squared tests[88] (following Lu, Maekawa and Lee, 2008) to identify any break points not indicated in the Chow test (reported in the chapter appendix). This is done as there may be some delayed impact of these events on the indices. The null hypothesis for each test is: no breaks at specified breakpoints.

Table 3.29 Chow test with break point at 5/9/2008 for the returns on the South African market index

F-statistic	1.858819	Prob. F(1,573)	0.1733
Log likelihood ratio	1.862288	Prob. Chi-square(1)	0.1724
Wald statistic	1.858819	Prob. Chi-square(1)	0.1728

Table 3.30 Chow test with break point at 14/1/2011 for the returns on the South African market index[89]

F-statistic	1.221245	Prob. F(1,573)	0.2696
Log likelihood ratio	1.224203	Prob. Chi-square(1)	0.2685
Wald statistic	1.221245	Prob. Chi-square(1)	0.2691

Table 3.31 Chow test with break point at 5/9/2008 for the returns on the emerging African market index

F-statistic	11.42847	Prob. F(1,573)	0.0008
Log likelihood ratio	11.35549	Prob. Chi-square(1)	0.0008
Wald statistic	11.42847	Prob. Chi-square(1)	0.0007

Table 3.32 Chow test with break point at 14/1/2011 for the returns on the emerging African market index[90]

F-statistic	4.991198	Prob. F(1,573)	0.0259
Log likelihood ratio	4.986931	Prob. Chi-square(1)	0.0255
Wald statistic	4.991198	Prob. Chi-square(1)	0.0255

Table 3.33 Chow test with break point at 5/9/2008 for the returns on the emerging African market excluding South Africa index

F-statistic	13.16191	Prob. F(1,573)	0.0003
Log likelihood ratio	13.05844	Prob. Chi-square(1)	0.0003
Wald statistic	13.16191	Prob. Chi-square(1)	0.0003

[87] The CUSUM test (Brown, Durbin, and Evans, 1975) is based on the cumulative sum of the recursive residuals. This option plots the cumulative sum together with the 5% critical lines. The test finds parameter instability if the cumulative sum goes outside the area between the two critical lines.

[88] The CUSUM of squares test (Brown, Durbin, and Evans, 1975) provides a plot of the test statistic S_t against time t and the pair of 5 percent critical lines. As with the CUSUM test, movement outside the critical lines is suggestive of parameter or variance instability.

[89] Test results for CUSUM test and CUSUM of squared test on the South African asset portfolio returns are in appendix chapter A3.18 and A3.19 respectively.

[90] Test results for CUSUM test and CUSUM of squared test on the Emerging African asset portfolio returns are in appendix chapter A3.20 and A3.21 respectively.

Table 3.34 Chow test with break point at 14/1/2011 for the returns on the emerging African market excluding South Africa index[91]

F-statistic	5.079758	Prob. F(1,573)	0.0246
Log likelihood ratio	5.075026	Prob. Chi-square(1)	0.0243
Wald statistic	5.079758	Prob. Chi-square(1)	0.0242

Table 3.35 Chow test with break point at 5/9/2008 for the returns on the frontier African market index

F-statistic	5.294851	Prob. F(1,573)	0.0217
Log likelihood ratio	5.288933	Prob. Chi-square(1)	0.0215
Wald statistic	5.294851	Prob. Chi-square(1)	0.0214

Table 3.36 Chow test with break point at 14/1/2011 for the returns on the frontier African market index[92]

F-statistic	0.516773	Prob. F(1,573)	0.4725
Log likelihood ratio	0.518343	Prob. Chi-square(1)	0.4715
Wald statistic	0.516773	Prob. Chi-square(1)	0.4722

From the results of the Chow test above, I observe a variation on the impact of the 2008 financial crisis and the Arab Spring on the asset indices formed. Within the South African market, I cannot reject the null hypothesis of no breaks at the specified breakpoints (Tables 3.45 and 3.46). The CUSUM test (chapter appendix A3.17) also verifies this finding and also indicate a stable time-series through the sample period. However, the more robust CUSUM of squared test (chapter appendix A3.18) is suggestive of parameter instability, although these changes are not on the particular dates (5/9/2008 and 14/1/2011) being tested.

For the returns on the asset portfolio within the emerging African market, I reject the null hypothesis of no breaks at the specified breakpoints as I observe some instability in the data as indicated by the Chow test in Table 3.47 for the 2008 financial crisis and Table 3.48 for the Arab Spring. This is further confirmed by the CUSUM and CUSUM of squared tests in chapter appendices A3.19 and A3.20, respectively.

When South Africa is excluded from the emerging African market index, the results of the Chow test (Table 3.49 for the 2008 financial crisis and Table 3.50 for the Arab Spring) show that the null hypothesis of no breaks at the specified breakpoints is rejected. The CUSUM test

[91] Test results for the CUSUM test and CUSUM of squared test on the emerging Africa ex South Africa asset portfolio returns are in chapter appendices A3.22 and A3.23, respectively.
[92] Test results for the CUSUM test and CUSUM of squared test on the frontier African asset portfolio returns are in chapter appendices A3.24 and A3.25, respectively.

and CUSUM of least squares test (chapter appendix, Figures A3.21 and A3.22, respectively) provide some support for this result.

Lastly, within the frontier African market, the results of the Chow test demonstrate that the null hypothesis is rejected for the 2008 financial crisis, but cannot be rejected for the Arab Spring (Table 3.51 for the 2008 financial crisis and Table 3.52 for the Arab Spring). The CUSUM test and particularly the CUSUM of least squares test (chapter appendix, Figures A3.23 and A3.24, respectively) support this as I find no break in the CUSUM of least square graph at or around the 14/1/2011 mark for the Arab Spring.

This provides further evidence on potential instability in the estimates of the unconditional asset-pricing models. This supports the discussion in Chapters 5, 6, 7 and 8 on the impact of the contagion dummy variables within the static CAPM model. Following these findings, I also investigate the impact of time variation on asset-pricing estimates in Chapter 6.

3.8.5 Conditional CAPM

According to the CAPM, any difference in beta, which measures the difference in an assets exposure to systematic risk, should explain any difference in expected returns on the asset. The Sharpe-Lintner-Black CAPM remains one of the most used asset-pricing models in describing how investors assess risk. However, it has come under increased scrutiny as it does not account for returns of portfolios sorted by size, value, momentum and liquidity, as identified in Fama and French (1992), Carhart (1997) and Wang and Chen (2012).

One of the commonly made assumptions of the static CAPM is that the betas of assets remain constant over time, which is quite unrealistic given that the business cycle will present variations to a firm’s cash flow and also the degree of a firm’s financial leverage, hence a varying relative risk, as highlighted in Jagannathan and Wang (1996). This implies that in theory, the CAPM could hold conditionally on time information, period by period, even when the unconditional CAPM does not hold.

This implies that the CAPM can hold in the different regimes identified in Section 3.8.4 above, but still not hold unconditionally, although the tendency of the CAPM to hold in different regimes improves drastically compared to the unconditional whole period CAPM. This failure of the CAPM to account for time variation may have led to its poor performance as identified in Adrian and Franzoni (2009). This unconvincing empirical evidence of the static CAPM may well be due to *systematic stochastic changes* affecting the environment that generate returns as observed in Chan and Lakonishok (1993), Black (1993) and Jagannathan and Wang (1996). The size and B/M effects identified in Fama and French (1992) could be explained by time-varying beta as observed by Zhang (2005), Lustig and Van Nieuwerburgh (2005) and Santos and Veronesi (2006).

Studies of the conditional CAPM in the emerging markets suggest that exposure to the common risk factor is low, hence the static CAPM performs poorly in explaining expected cross-sectional returns. According to Harvey (1994), emerging markets are mostly influenced by local information sets rather than global information sets. This is because most emerging and African markets are segmented from the world capital markets, as identified in Kim and Singal (2000), Bekaert and Harvey (2000) and Bekaert (1995); hence the implicit assumption that the world capital markets are completely integrated does not hold. Harvey (1994) also identified that risk loadings in emerging markets are not constant, as suggested by many researchers in developed markets, as they are time-varying in emerging markets.

Although a good number of papers have investigated asset-pricing models, the emphasis has often been on developed markets and some emerging markets, with only a very thin and segmented emphasis on investigating the African market. This is probably due to the relative newness of the financial markets in Africa. According to Alagidede (2008), this may also be due to the perceived high riskiness of the African market due to the underdevelopment of the institutional environment in which the financial markets operate and the high illiquidity of the market. However, in light of the growth of the African markets and their often superior performance in recent years, as identified in Cheng et al. (2010), there is an obvious gap in the literature.

In recent decades, the stability of beta over time has been a subject of increasing research. In his seminal article, Blume (1971) highlighted the tendency of beta to mean-revert. In the US, Fabozzi and Francis (1978) identified that most US equities have time-varying betas. This is supported by Collins et al. (1987), Simmonds et al. (1986) and Bos and Newbold (1984), who suggest that over a five to 10-year period, between 2% and 58% of US stocks have varying betas. According to Pope and Warrington (1996) and Faff and Brooks (1997), between 11% and 61% of Australian stocks are time-varying over a five to 10-year estimation period. This is supported by the findings of Faff et al. (1992) and Brooks et al. (1992). Other researchers who find beta to be unstable in other countries include Abuzar and Shah (2002), Oran and Soytas (2008) and Tunçel (2009). However, Altman et al. (1974), Baesel (1974) and Roenfeldt (1978) insist that the betas will become more stable with longer estimation periods.

As stated in Brooks et al. (1998), some literatures believe in the microeconomic nature of varying betas, hence highlighting an ability to diversify away its effects through the formations of a portfolio; other evidences disclose that this is not so (see Collins et al., 1987, and Brooks et al., 1992, 1994). Thus, the instability of betas could well be due to macroeconomic factors or “noise” from portfolio formations, as explained in Brooks et al. (1998). If the existing literature mostly focuses on the developed market due to the problems raised by beta instability, there should be even more interest in emerging markets as the effects are more likely to be more significant, and even more in the African markets. However, research on beta instability in the African market continues to be very thin. Given that the effect of varying beta could be greater in the African market, I account for beta instability within the analysis.

There are a number of techniques that exist in the literature for the modelling and estimation of time-varying beta. These are broadly based on observable economic factors used in modelling variations in beta using econometric models, and the estimation of beta series using time-series models, though these beta estimates are provided from internal structure in the data. The macroeconomic models estimate beta coefficient as a function of economic variables such as oil prices, inflation, trade deficit, budget deficit and interest rates, as identified in Abell and Kreuger (1989). Other studies that follow this procedure include Shanken (1990) and Faff and Brooks (1998). The generalised autoregressive conditional heteroscedasticity (GARCH) time-series model will be used in modelling time-varying betas in this study. Other prominent time-series modelling techniques include the Schwert and Seguin model and the Kalman filter algorithm, and are discussed in the next sections.

As identified in Bali and Engle (2010), the version of the Sharpe (1964) and Lintner (1965) CAPM model which is a time-varying conditional model that relates the conditionally expected excess returns of the risky asset to the conditionally expected excess return on the market portfolio, is denoted as:

$$E\left(R_{i,t+1}\middle|\Gamma_t\right) = \frac{E(R_{m,t+1}|\Gamma_t)}{var(R_{m,t+1}|\Gamma_t)} . cov\left(R_{i,t+1}, R_{m,t+1}\middle|\Gamma_t\right) \quad (3.25)$$

The expected conditional beta $E\left(\beta_{i,t+1}\middle|\Gamma_t\right)$ is represented by the ratio of $cov\left(R_{i,t+1}, R_{m,t+1}\middle|\Gamma_t\right)$ to $var\left(R_{m,t+1}\middle|\Gamma_t\right)$,

$$E(\beta_{i,t+1}|\Gamma_t) = \frac{cov(R_{i,t+1}, R_{m,t+1}|\Gamma_t)}{var(R_{m,t+1}|\Gamma_t)} \quad (3.26)$$

where, according to Bali and Engle (2010), $\frac{E(R_{m,t+1}|\Gamma_t)}{var(R_{m,t+1}|\Gamma_t)}$ represents the reward/risk ratio, which is also the relative risk-aversion coefficient, as noted in Merton (1980). $R_{i,t+1}$ is the return on the risky asset i in excess of the risk-free interest rate ($R_{i,t+1} = r_{i,t+1} - r_f$), while $R_{m,t+1}$ is the aggregate wealth portfolio of all assets in the economy, represented as the market portfolio m in excess of the risk-free interest rate ($R_{m,t+1} = r_{m,t+1} - r_f$). The common information set available to the investors at time t is represented as Γ_t, which is the information set that investors use to form expectations of future returns. The expected excess return on the risky asset i conditional on information set Γ_t at time $t + 1$ is represented as $E(R_{i,t+1}|\Gamma_t)$, while $E(R_{m,t+1}|\Gamma_t)$ represents the expected excess return on the market portfolio conditional on the information set Γ_t at time $t + 1$, $var(R_{m,t+1}|\Gamma_t)$ is the expected conditional variance of excess returns on the market at time $t + 1$ given information set Γ_t, and $cov(R_{i,t+1}, R_{m,t+1}|\Gamma_t)$ is the expected conditional covariance between excess returns on the risky asset and the market portfolio at time $t + 1$ given information set Γ_t.

However, the fundamental nature of a single-factor CAPM has been a subject of immense debate with Fama and French (1992) showing that size and value are priced, but not the conventionally estimated beta. Fama and French (1993) proposed a three-factor, asset-pricing model that seemed to adequately describe the average stock excess returns. According to Fama and French (1996), the three-factor model also explains long-term return reversals, but not the short-term return continuation (momentum) anomaly. Recent literature has also identified the inability of the three-factor model to explain the liquidity premium (see Lam and Tam, 2011, and Lee, 2011). This is particularly severe in emerging and African markets as identified in Claessens and Dasgupta (1995). Also, recent research in the emerging markets and particularly in the African markets insists that the value premium is insignificant, as identified in Loughran (1997), Wang and Xu (2004) and Shum and Tang (2005).

Even where the intertemporal behaviour of the market risk premium is used, most researchers employed the conditional single-factor model motivated by the static CAPM of Sharpe (1964) and Lintner (1965). The implication of these single-factor conditional models is a proportional or simple linear relation between conditional market variance and market risk premium. However, the findings using these conditional single-factor models have been mixed, with

Campbell (1987) and Glosten et al. (1993) finding a significant negative relation between risk and return, and Harvery (1989) and Baillie and DeGennaro (1990) finding a significant positive relation. The multifactor model within this paper assumes that there is a partial relation between risk premium and conditional market variance; hence, if this assumption becomes "true", the estimates of conditional single-factor models suffer from omitted variable bias and will be misspecified. This research will explore whether a conditional multifactor model explains the conditional behaviour of asset prices better than the single-factor models used in existing literature.

Following these studies, this research will incorporate conditioning information into a four-factor model that includes excess market returns, the average returns of small firms minus the average returns of big firms (size), the contemporaneous average returns on a short-term winner portfolio minus the average returns on a short-term loser portfolio (momentum) and the contemporaneous average returns on a portfolio of illiquid stocks minus the average returns of liquid stocks (liquidity). In using a conditional four-factor model, I consider that in a dynamic world, the prices of risk and indeed risk exposures are likely to depend on conditioning information and hence will vary over time. Equation 3.26 can be extended to a conditional four-factor model and can be written as:

$$E\left(R_{i,t+1}\middle|\Gamma_t\right) = \beta_{M,t}E\left(R_{M,t+1}\middle|\Gamma_t\right) + \beta_{s,t}E(SMB_{t+1}|\Gamma_t) + \beta_{m,t}E(WML_{t+1}|\Gamma_t) + \beta_{p,t}E(IMV_{t+1}|\Gamma_t), \quad (3.27)$$

where $R_{i,t+1}$ is the return on the risky asset i in excess of the risk-free interest rate ($R_{i,t+1} = r_{i,t+1} - r_f$), $R_{M,t+1}$ is the aggregate wealth portfolio of all assets in the economy represented as the market portfolio m in excess of the risk-free interest rate ($R_{M,t+1} = r_{M,t+1} - r_f$), SMB_{t+1} is the returns of a mimicking portfolio based on size, $WML_{t+1}$is the return of a mimicking portfolio based on momentum, IMV_{t+1} is the return of a mimicking portfolio based on liquidity, the information set is represented by Γ_t, $E[.|\Gamma_t]$ is the conditional expectation based on information as at time t, $\beta_{M,t}$ is the relative risk, $\beta_{s,t}$ is the state risk arising from investors' special hedging concerns associated with size; $\beta_{m,t}$ is the risk arising from special hedging concerns related with momentum and $\beta_{p,t}$ is the risk arising from investors' special hedging concerns associated with illiquidity.

An alternative specification of the conditional Fama-French model is identified in Wu (2002) as:

$$E(R_{i,t+1}|\Gamma_t) = \psi_{M,t}cov(R_{i,t+1}, R_{M,t+1}|\Gamma_t) + \psi_{s,t}cov(R_{i,t+1}, SMB_{t+1}|\Gamma_t) + \psi_{m,t}cov(R_{i,t+1}, WML_{t+1}|\Gamma_t) + \psi_{p,t}cov(R_{i,t+1}, IMV_{t+1}|\Gamma_t), \quad (3.28)$$

where $\psi_{M,t}$ is the reward to covariability with the market (the price of the market risk); $\psi_{s,t}$ is the reward to covariability with SMB_{t+1} (the price of the state risk associated with size); $\psi_{m,t}$ is the reward to covariability with WML_{t+1}, (the price of the state risk associated with momentum) and $\psi_{p,t}$ is the reward to covariability with IMV_{t+1} (the price of the state risk associated with illiquidity). The expectation in a conditional approach is that the price risks and covariances are supposed to be time-varying. Following from Equation 3.28 and the risk loadings identified in Wu (2002), I hypothesise that the risk loadings are linear functions of a set of conditioning information as shown in the following regression:

$$R_{i,t+1} = \alpha + \mathbf{Z}_t\boldsymbol{\beta}_M R_{M,t+1} + \mathbf{Z}_t\boldsymbol{\beta}_s SMB_{t+1} + \mathbf{Z}_t\boldsymbol{\beta}_m WML_{t+1} + \mathbf{Z}_t\boldsymbol{\beta}_p IMV_{t+1} + \varepsilon_{i,t+1} \quad (3.29)$$

The total excess return on portfolio i is denoted as $R_{i,t+1}$ while $R_{m,t+1}$ is the market portfolio m in excess of the risk-free interest rate, SMB_{t+1} and IMV_{t+1} are returns on portfolios sorted by size and liquidity, $\mathbf{Z}_t$ is a row of vectors while α, $\boldsymbol{\beta}_M$, $\boldsymbol{\beta}_s$, $\boldsymbol{\beta}_m$ and $\boldsymbol{\beta}_p$ are constant weights. The conditional risk loadings on R_M, SMB, UMD and IMV are $\mathbf{Z}_t\boldsymbol{\beta}_M$, $\mathbf{Z}_t\boldsymbol{\beta}_s$, $\mathbf{Z}_t\boldsymbol{\beta}_m$ and $\mathbf{Z}_t\boldsymbol{\beta}_p$, respectively. The abnormal return is usually α, the intercept.

In a dynamic economy, rational risk-averse investors will normally expect and hedge against the possibility that investment opportunities may change adversely in the future. Due to this hedging possibility of a dynamic economy, the expectation will be that the conditionally expected return on an asset will be jointly linear in the conditional market beta and the hedge portfolio betas, as identified in Jagannathan and Wang (1996).I assume that the motivation for hedging within this dynamic economy is still sufficient, following Merton (1980).

3.8.5.1 GARCH models

As explained in Mills (1996), once the linear assumption of the CAPM is relaxed, several possible ways of modelling a time-series emerge, covering such classes as chaotic dynamics in Hsieh (1991) and conditional heteroscedasticity models in Bollerslev, Chou and Kroner (1992).

Setting $\Delta\log P_t$ as the returns of a stock, the AR(p) model is then

$\varphi_p(\mathrm{L})\ \Delta\log P_t = \delta_t$ (3.30) where the AR polynomial in L of order p is φ_p(L) = 1 - $\varphi_1 L - \cdots - \varphi_p L^p$ and δ_t satisfies the white noise properties $E[\delta_t] = 0, E[\delta_t^2] = \sigma^2$ and $E[\delta_t \delta_s] = 0, \forall_s \neq t$.

But investors' attitudes towards risk and expected return are non-linear; also, the process by which information is incorporated into security prices and the interactions among market participants are all inherently non-linear. As stated in Alagidede (2011), an array of tests can be used since nonlinearity occurs in many forms and hence the following tests can be considered: GARCH of Engle (1982) and McLeod and LI (1983), BDS test for randomness by Brock, Dechert, Scheinkman and LeBaron (1996), the threshold effects of Tsay (1986) and the bicovariance test of Hinich and Patterson (1995) and Hinich (1996). The exponential GARCH-M will be fit where the mean equation is specified as

$$\Delta \log P_t = \gamma + \sum \varphi_i \Delta \log P_{t-1} + \sqrt[\omega]{h_t} + \delta_t \; \delta_t \Omega_{t-1} \sim \mathrm{NID}(0, \mathrm{h_t}) \text{ (3.31)}$$

where $\delta_t = \sqrt[z_t]{h_t}$ and Z_t is independent and identically distributed with mean and unit variance of zero. The conditional variance $|h_t|$ is represented as

$$\text{In } (h_t) = \partial + \sum_{i=1}^{q} \alpha_i g(z_{t-1}) + \sum_{j=1}^{p} \beta_j \text{In}(h_{t-j}) \text{ (3.32)}$$

where $g(z_t) = \theta z_t + \zeta[|Z_t| - E|z_t|], z_t = \varepsilon_t / \sqrt{h_t}. \, g(z_t)$ has 1 ($\zeta = 1$) set as its coefficient. The risk premium can be examined by setting the conditional mean in Equation 18 as a function of the conditional variance. Hence, as Alagidede (2011) illustrates, I am able to check whether investors are rewarded for taking on more risk with extra returns. To account for asymmetry effect in the volatility process, an EGARCH model can be specified, as identified in Black (1976), Nelson (1991), Glosten, Jagannathan and Runkle (1993) and Christie (1982).

Often, Equation 3.32 produces evidence in empirical research that the conditional volatility process is highly persistent and may also not be covariance-stationary. This suggests that it may be more suitable to have a model in which shocks have permanent effect on volatility. To achieve this, fractionally integrated GARCH (FIGARCH) can be applied; this can be particularly used to examine persistence in the variance and long memory. The FIGARCH (p, d, q) model of the conditional variance can be established as an autoregressive, fractionally integrated, moving average (ARFIMA) model applied to squared innovations, as noted in Baillie, Bollerslev and Mikkelsen (1996) as:

$$\big(1 - \alpha(L)\big)(1 - L)^d \delta_t^{\,2} = \partial + \big(1 - \beta(L)\big) v_t \text{ (3.33)}$$

where $\alpha(L)$ and $\beta(L)$ are polynomials of order q and p, and 0<d<1 is the fractional integration parameter. The FIGRCH (p, d, q) model can be expressed as follows after defining $v_t = \varepsilon_t^2 - h_t$ and rearranging Equation 3.33:

$$h_t = \partial + \beta(L)h_t + \left(1 - \beta(L) - \left(1 - \alpha(L)\right)(1 - L)^d\right)\delta_t^2 \quad (3.34)$$

Decoupling of the short-run and long-run movements in volatility is the main advantage of the FIGARCH, as stated in Alagidede (2011). The lag polynomials capture the short-run component, while the fractional differencing parameter d captures the long-run component. In cases where $d = 0$, the FIGARCH becomes the standard GARCH model.

3.8.5.2 The GARCH model applied

With the incremental benefits of other time-varying models over the standard GARCH model quite minute, this study will be using the GARCH-based model. The Sharpe-Lintner CAPM assumes returns to be IID, although stylised facts within empirical finance literature highlight that returns in many financial markets show signs of autocorrelation with regularly observed volatility clusters, where volatile periods with large absolute returns are followed by periods of small absolute returns. To extract conditional moments and betas for a variety of test portfolios, this research will extend the multivariate GARCH parameterisation to accommodate GARCH-in-mean effects, as proposed in Ding and Engle (1994). This follows the M-GARCH model first proposed by Bollerslev (1986), which derives the time-series of beta indirectly from estimates of the expected conditional covariance between excess returns on the risky asset and the market portfolio, and the expected conditional variance of excess returns on the market, in Equation 3.26.

$$E\left(\beta_{i,t+1}\middle|\Gamma_t\right) = \frac{cov\left(R_{i,t+1}, R_{m,t+1}\middle|\Gamma_t\right)}{var\left(R_{m,t+1}\middle|\Gamma_t\right)} \quad (3.36)$$

It was subsequently extended to capture the dynamics of autoregressive means and volatility process for valuation in stock options, as noted in Ritchken and Trevor (1999), along with further extensions by Engle (2001) for a variety of applications in the areas of stock price and equity indices volatility.

The GARCH model is generally denoted as GARCH (u, v), which is interpreted as a generalisation of Engle's (1982) ARCH (u) model obtained by including v moving average terms in the autoregressive equation for the conditional expectation. As detailed in Engle and Bollerslav (1986) and Bollerslav (1987), the time-series technique of Box and Jenkins (1976) can be applied to the correlations and the autocorrelations for the squared process, which will be used to identify the orders of u and v.

The use of GARCH-based methods of modelling time-varying beta has been quite dominant in the literature and utilised in various studies, including Giannopoulos (1995), who used a bivariate GARCH-in-mean model to identify the time-series properties of, initially, the total risk of security and subsequently the systematic and nonsystematic components. Brooks et al. (1997b) also captured conditional betas using a bivariate specification of the M-GARCH model. Li (2003) found the GARCH model to be the most favoured for out-of-sample forecasting. Marti (2006) used an asymmetric beta model, a macroeconomic variable model, the Schwert and Segun model, the Kalman filter, GARCH models and the rolling regressions, although the study finds that the Kalman filter with beta being specified as a random walk performs best. And lastly, Choudhry and Wu (2007) tested the forcasting ability of four different GARCH models (bivariate GARCH, BEKK GARCH, GARCH-GJR and the GARCH-X model) and the Kalman filter model.

This study also applies an innovation of the dynamic conditional correlations based on a GARCH-type model (see Chapter 7) and a variant of the GARCH-GJR.

3.8.6 Potential alternative methods for a conditional-type CAPM

3.8.6.1 The threshold CAPM

Emphasising the importance of understanding the dynamics of time variation in betas, Akdeniz, Salih and Caner (2003) developed the threshold CAPM. They highlight that despite the widely accepted premise of time variation in expected return and betas, there still remains to be seen a consensus on the way to model time variation. Modelling of time variation takes the form of continuous approximation of the conditional CAPM, which Ghysels (1998) refutes as ineffective. He argues that time variation in beta is slower than the conditional CAPM suggests. Arisoy, Altay-Salih and Akdeniz (2011) developed a model where beta changes slowly and discretely in time. They propose a volatility-based threshold CAPM where asset betas change with respect to investors’ assessment of aggregate risk conditions.

Within the threshold CAPM, investors re-evaluate the riskiness of an asset when the aggregate volatility goes beyond a certain threshold. It also allows for time variation in aggregate volatility, allowing beta to change contemporaneously with the changes in aggregate volatility. Lastly, Hansen's (2000) threshold regression methodology is used to test volatility-related regime changes in beta risk. The threshold volatility CAPM developed in Arisoy, Altay-Salih and Akdeniz (2011) is represented as

$$r_{i,t+1} = \left(\alpha_1 1_{\{z_t \leq \lambda\}} + \alpha_2 1_{\{z_t > \lambda\}}\right) + \left(\beta_1 1_{\{z_t \leq \lambda\}} + \beta_2 1_{\{z_t > \lambda\}}\right) r_{m,t+1} + \varepsilon_{i,t+1} \quad (3.37)$$

where

$r_{i,t+1}$ = the excess return on asset i,

$r_{m,t+1}$ = the excess return on the market portfolio,

β_t captures time variation in market betas,

z_t = the conditioning information on investors' assessment of aggregate volatility risk,

$1_{\{\}}$ = the indicator function,

λ = the threshold parameter for aggregate volatility.

3.8.6.2 Kalman filter-based approaches

As stated in Mergner and Bulla (2005), the time-varying structure of the beta can be modelled directly through a state space approach. This is in contrast to other techniques based on volatility, which require the estimation of conditional variance of asset i and the market to be obtained first before the conditional beta series can be constructed. The state-based models are estimated numerically, based on an assumption of normality, through a recursive algorithm known as the Kalman filter. For more details on the Kalman filter and its application, see Meinhold and Singpurwella (1983) or Harvey (1989). In the state space form, an observation equation is construed from the excess returns market model of Sharpe and Lintner.

$$R_{it} = \alpha_{it} + \beta_{it} R_{Mt} + \varepsilon_{it} \quad (3.38)$$

With the α_{it} treated as zero, the equation becomes an observable equation:

$$R_{it} = \beta_{it} R_{Mt} + \varepsilon_{it} \quad (3.39)$$

where the state equation

$$\beta_{it} = \vartheta_i \beta_{it-1} + \eta_{it} \text{ (3.40)}$$

defines the dynamic process of the unobserved time-varying state vector, β_{it}, with the constant transmition parameter denoted as ϑ_i. The state equation error η_{it} and the observation error ε_{it} are assumed to be Gaussian:

$$E(\epsilon_{it}\epsilon'_{i\tau}) = \begin{cases} \sigma_i^2, for\ t = \tau \\ 0, otherwise, \end{cases} \text{ (3.41)}$$

$$E(\eta_{it}\eta'_{i\tau}) = \begin{cases} \sigma_{\eta i}^2, for\ t = \tau \\ 0, otherwise, \end{cases} \text{ (3.42)}$$

and to be uncorrelated at all lags:

$E(\epsilon_{it}\eta'_{i\tau}) = 0$ for all t and τ. (3.43)

The hyper-parameters of the system are ϑ_i, which is the transition parameter, and σ_i^2 and $\sigma_{\eta i}^2$ which are the constant variances. With different assumptions on ϑ_i, a number of alternative specifications of the stochastic process of β_{it} may be derived. By setting ϑ_i to unity, Mergner and Bulla (2005) represents the first state space specification of the evolution of the time-varying beta as a random walk (RW) model. The beta coefficient is a RW model

$$\hat{\beta}_{it}^{KFRW} = \beta_{i,t-1} + \eta_{it} \text{ (3.44)}$$

where the two hyper-parameters σ_i^2 and $\sigma_{\eta i}^2$ have to be estimated. See Doornik (2001) for further details. (Doornik (2001) used 0 x 3.30 together with the package SsfPack by Koopman et al. (1999) to compute the KF models). A mean-reverting model can also be used for the model time-varying beta process. An autoregressive process of the order AR (1), with a constant mean can be used within a mean-reverting (MR) model:

$$\hat{\beta}_{it}^{KFMR} = \bar{\beta}_i^* + \vartheta_i \beta_{i,t-1} + \eta_{it} \text{ (3.45)}$$

with the AR (1) parameter $|\vartheta_i|< 1$ and a constant $\bar{\beta}_i^*$. To allow for significant economic interpretation, which can allow $\bar{\beta}_i$to be the mean beta over the entire sample and ϑ_i to measure speed of mean revision of the time-varying beta, Equation 3.45 can be rearranged as:

$$\hat{\beta}_{it}^{KFMR} = \bar{\beta}_i + \vartheta_i(\beta_{i,t-1} - \bar{\beta}_i) + \eta_{it} \text{ (3.46)}$$

where all of σ_i^2,$\sigma_{\eta i}^2$, $\bar{\beta}_i$ and ϑ_i will be estimated. For further evidence on the speed parameter, see Faff at al. (2000) and Yao and Gao (2004).

3.8.6.3 Stochastic volatility conditional betas

Another alternative approach of modelling time-varying beta includes the addition of contemporaneous shock to the return variance, as identified in Taylor (1986). These models are otherwise known as SV models. These differ from the GARCH framework in that with a GARCH framework with only one error term, the conditional mean and conditional volatility of the return series are characterised by the same shock. The SV models can qualify as a better model for describing financial time-series as they imply excess kurtosis and have a higher degree of flexibility. According to Mergner and Bulla (2005), the first two moments are usually used to represent the SV model. The mean equation is given as:

$$R_{it} = \mu_{it} + \sigma_{it}\epsilon_{it}, \epsilon_{it} \sim NID(0,1), t = 1, \ldots, T, (3.47)$$

where R_{it} is the return series of index i and μ_{it} is the expectation of R_{it}. The mean is usually taken to be zero for SV models or modelled before estimating the volatility process, as stated in Hol and Koopman (2002). As seen in Kim et al (1998), other authors use the mean-corrected returns R_{it}^* as an alternative, where

$$R_{it}^* = \ln(P_{it}) - \ln(P_{i,t-1}) - (1/T)\sum_{i=0}^{T}(\ln(P_{it}) - \ln(P_{i,t-1})), (3.48)$$

The disturbances are assumed to be IIND with zero mean and unit variance. The variance equation is given as

$$\sigma_{it}^2 = \sigma_{it}^{*2}\exp(\upsilon_{it}), \ (3.49)$$

where the product of a positive scaling factor σ^{*2} and the exponential of the stochastic process $\upsilon_{it}$is the actual volatility σ_{it}^2, which is modelled as a first-order autoregressive process:

$$\upsilon_{it} = \phi_i\upsilon_{i,t-1} + \sigma_{\eta i}\eta_{it}, \eta_{it} \sim NID\left(0, \frac{\sigma_\eta^2}{1-\phi_i^2}\right), (3.50)$$

To ensure stationarity of υ_{it} the persistence parameter ϕ_i is restricted to be positive and smaller than one. ϵ_{it} and η_{it} are assumed to be uncorrelated, contemporaneously and at all lags. A good interpretation of these two different shocks is identified in Franses and van Dijk (2000), where η_{it} represents the shocks to the intensity of the flow of news and ϵ_{it} reflects the content of new information (good or bad news). The parameters of the SV model cannot be estimated by directly applying the standard maximum likelihood techniques. This is due to the addition of an unobservable shock to the return variance, which makes the variance a latent process, making it impossible to characterise the variance explicitly with respect to observable past information.

The estimation of SV models has followed various procedures as identified within the literature. Some of these procedures include the Monte Carlo likelihood (MCL) estimator presented in Danielsson (1994), the efficient MCL proposed by Sandmann and Koopman (1998), a Bayesian Monte Carlo Markov Chain (MCMC) procedure developed by Jacquier et al. (1994), a quasi-maximum likelihood presented in Harvey et al. (1994) and the moments estimators proposed by Melino and Turnbull (1990). However, Mergner and Bulla (2005) highlight that these volatility models are very rarely used in practice due to the lack of consensus on estimating the models. One process that is prevalent is that of Mergner and Bulla (2005), which estimates the SV models using the efficient MCL technique, which is less computationally intense but still with finite sample performance that compares well with those of MCMC. Mergner and Bulla's (2005) process follows the procedure developed in Doornik (2001) and the package in Koopman et al. (1999). With estimates of σ_{0t}^2 and σ_{it}^2 obtained, the time-varying beta can be constructed using:

$$\hat{\beta}_{it}^{SV} = \frac{\sigma_{0i}\sigma_{it}}{\sigma_{0t}}. (3.51)$$

3.8.6.4 The Markov switching approach

The Markov switching model introduced by Hamilton (1989) is also known as the regime-switching model within a broader class of state space models. It involves the characterisation of the time-series behaviours of different regimes using multiple structures (equations). By allowing switching between these structures, the model is able to capture more complex dynamic patterns. This follows an implicit assumption that data results from a process that undergoes sudden changes. The systematic risk of an asset is determined by the beta within the regimes where the switching mechanism is controlled by an unobserved state variable that follows the Markov chain. This differs from a structural change model that allows only occasional and exogenous changes, unlike the Markov switching model, which allows frequent changes at random time points. According to Mergner and Bulla (2005), the switching behaviour of a beta is governed by a transition probability matrix (TPM). Within a two-state model assumption, the TPM will take the form of:

$$\Gamma = \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix}, (3.52)$$

where γ_{11} represents the probability of staying in the first state from period t to period $t+1$, and γ_{12} is the probability of switching from the first to the second state. The second row of the Γ can be interpreted analogously. Following the process explained in Mergner and Bulla(2005), two Markov switching (MS) models are used, where the first is a simple MS regression model constructed as follows: let the state sequence representing the different regimes be denoted as $\{s_1, \ldots, s_T\}$ and be driven by the TPM of a stationary Markov chain; the states take values in $\{1, \ldots, m\}$. The regime-switching CAPM follows Huang (2000) and is denoted as:

$$R_{it} = \alpha_{is_t} + \beta_{is_t} R_{0t} + \eta_{it}, \eta_{it} \sim N\left(0, \sigma_{is_t}^2\right), (3.53)$$

where the value of state s_t determines the regression coefficient $(\alpha_{is_t}\beta_{is_t})$ to be selected. This is also designed to accommodate both the serial correlations of the individual series as well the correlations across returns series. The Markov switching market (MSM) model is the second approach, where there are more assumptions on the market returns to harmonise the switching times of beta with different market conditions. The hidden Markov model with normal or double-exponential variables can govern the temporal and distributional properties of daily returns series, as shown in Rydan et al. (1998). They identify that the dynamics of assets returns follow the same equation (3.53) with the distribution of the market returns being given by:

$$R_{0t} = \mu_{s_t} + \epsilon_{it}, \epsilon_{it} \sim N\left(0, \sigma_{0s_t}^2\right), (3.54)$$

This shows the synchronous behaviour that allows for direct conclusions from the market conditions on the asset's risk represented in the beta. This is because in the MSM model, the regime of the market changes together with the regime of the regression setup as they depend on the same state sequence.

MSMs are based on the maximum likelihood method for hidden Markov models. Through numerical maximisation of the log-likelihood function, the parameters of the model can be estimated directly. This is because the likelihood L_T of both models is available in an explicit form (MacDonald and Zucchini, 1997, cf.). The estimates for the model parameters include among other things the state-dependent betas for each asset i and state j denoted by $\hat{\beta}_{ij}^{MS}$ or

$\hat{\beta}_{ij}^{MSM}$. To obtain in-sample estimates and out-of-sample forecasts of conditional betas, the information about the state distribution at t has to be derived. This is because the state sequence cannot be observed. As explained in Ephraim and Merhav (2002), through smoothing, filtering and state prediction algorithms, the desired probabilities of a sojourn in state j at time t can be computed. By weighting the state-dependent $\hat{\beta}_{ij}^{MS/MSM}$ with the probability of the sojourn in the corresponding state, estimates for the time-varying betas can be calculated given the state distribution at time t as:

$$\hat{\beta}_{ij}^{MS/MSM} = \sum_{j=1}^{m}\left[\beta_{ij}.P(s_t = j|R_{01},\dots,R_{0T},R_{i1},\dots,R_{0T})\right] \quad (3.55)$$

with

$$P(S_t = j|R_{01},\dots,R_{0T},R_{11},\dots,R_{1T}) = \begin{cases} \dfrac{\alpha_t(j)\beta_t(j)}{L_T} & for\ 1 \leq t \leq T \\ \dfrac{\alpha_t(j)(\Gamma^{t-1})_{\cdot j}}{L_T} & for\ T \leq t, \end{cases} \quad (3.56)$$

where $\alpha_t(j)$, $\beta_t(j)$ are the forward/backward probabilities from the forward-backward algorithm (Rabiner, 1989) and $(\Gamma^{t-1})_{\cdot j}$ denotes the jth column of the matrix Γ^{t-T}.

For more details on the Markov switching model, see Engle and Hamilton (1990), Goodwin (1993), Ghysels (1994) and Kim and Nelson (1998). Other variants incorporate the switching mechanism into conditional variance models, see Lam and Li (1998), Jacquier, Polson and Rossi (1994), Chen and Lin (1999) and Li, Hung and Kuan (2002).

3.9 Empirical models

The modelling procedure will follow a sequential development approach, starting with the Sharpe-Lintner CAPM as identified in Section 3.8.2. Although I expect returns in the African market to behave differently than suggested by the CAPM, this research will still examine the explanatory power of the CAPM in the African market. This is important given that the findings in the literature (See Jagannathan and Wang, 1993) suggest that the CAPM is still alive and well.

This study will also take into account the effect of size, book-to-market value, momentum and liquidity that offer improved performance in capturing anomalies across the cross-section of stock returns, as highlighted in the literature and in Section 3.8.2 above. The motivation is to examine whether the asset-pricing model, which includes factors for size (SMB), book-to-market value (HML), and momentum (UMD), can explain most of the variation in stock returns, following the findings in Fama and French (1992) and Carhart (1997).

The effect of liquidity has also been found to be very important in emerging/frontier markets, as seen in Hearn (2012) and Assefa and Mollick (2014). See also Section 2.4 in Chapter 2. This research will therefore employ a sequential model development approach using alternative pricing models. This approach was adapted from Carhart (1997) and Bartholdy and Peare (2005). I start off with the estimation of the standard CAPM:

$$R_i - R_f = \alpha_i + \beta_{iM}(R_M) - R_f) + \varepsilon_{it} \text{ (3.57)}$$

This model will then be extended by the SMB and HML factors to become the Fama-French three-factor model:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \beta_{is}SMB_t + \beta_{ih}HML_t + \varepsilon_{it} \text{ (3.58)}$$

The third model follows the Carhart four-factor model:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \varepsilon_{it} \text{ (3.59)}$$

This allows an investigation of whether size, book-to-market value and momentum are price factors on the African stock market.

These models are extended further to test for the importance of liquidity by incorporating the IMV factor in the time-series regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \varepsilon_{it} \text{ (3.60)}$$

Following Karus and Litzenberger (1976), Homaifar and Graddy (1988) and Fang and Lai (1997) and the rationale for accounting for higher moments, as highlighted in Section 2.10 of Chapter 2, I further augment the liquidity-adjusted Carhart (1997) four-factor model by incorporating the systematic measures of skewness and kurtosis. This is denoted as:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \beta_{ie}S_i + \beta_{ik}K_i + \varepsilon_{it} \quad (3.61)$$[93]

where S_i represents the systematic coskewness and K_i is the systematic cokurtosis of asset i.

As disclosed in Doan and Lin (2012), coskewness can be defined as the co-movement between an asset's return and the variance of the market portfolio, while cokurtosis refers to the co-movement between an asset's return and the skewness of the market portfolio.

3.9.1 Formation of portfolios

The asset portfolio ($R_i - R_f$):[94] The basic materials index asset portfolio for the emerging and frontier African markets, in the time-series regression, is formed following Sharpe (1964) and Lintner (1965) as:

$$R_i - R_f = \left(\frac{\sum_i^n R_{ie}}{n}\right) - R_f \quad (3.62)$$

where R_{ie} is the weekly return of each emerging/frontier African market index and R_f is the risk-free rate of return. n is the number of countries within emerging/frontier African markets.

The market portfolio ($R_m - R_f$):[95] The market portfolio is also formed following Sharpe (1964) and Lintner (1965) as follows:

$$R_m - R_f = (\sum_i^n R_{me_{adj}}) - R_f \quad (3.63)$$

where $R_{me_{adj}}$ is the weekly return on the market index of each emerging/frontier African market, adjusted by market capitalisation, and R_f is the risk-free rate of return. As noted in Bartholdy and Peare (2005), the underlying theory of the CAPM specifies that a value-weighted index consisting of all assets in the world be used. However, it is impossible to construct such index because only a small fraction of the assets in the world are traded on a

[93] See also Harvey and Siddique (2000) for higher-moment augmented models.
[94] The asset portfolios are identified in Section 3.3 above. Data source: Reuters Eikon and Datastream
[95] The market portfolios are identified in Section 3.3 above. Data source: Reuters Eikon and Datastream

stock exchange. Hence for this paper a value-weighted index that comprises the major stock exchange indices will be used as a proxy for the market index.

The size portfolio (SMB):[96] Following from Fama and French (1993), I construct six sub-portfolios (S/L, S/M, S/H, B/L, B/M, B/H). The size portfolio is formed as follows:

$$SMB = \left(\frac{\sum\left(\frac{S}{L}, \frac{S}{M}, \frac{S}{H}\right)}{3} \right) - \left(\frac{\sum\left(\frac{B}{L}, \frac{B}{M}, \frac{B}{H}\right)}{3} \right) \quad (3.64)$$

The size portfolio mimics the risk factor in returns related to size, which is the weekly difference between the same weighted simple average of the returns on S/L, S/M, and S/H, which are the three equal-weighted[97] small-stock portfolios, and the average of the returns on B/L, B/M, and B/H, which are the three equal-weighted big stock portfolios. As stated in Fama and French (1993), this will mean that the influence of book-to-market equity value should be largely absent from this difference, with the focus on the returns behaviour of the small and big stocks.

The small and big sub-portfolios were ranked based on the median of the market capitalisation of the firms on the last week of each holding semi-annual period, ending June and December of each sample year. The market capitalisation for each firm in each African market was extracted in dollars from Reuters Eikon to ensure that they are perfectly comparable. Hence firms with market capitalisation higher than the median are placed in the big sub-portfolio and those smaller are placed in the small sub-portfolio.

The median[98] market capitalisation was used instead of the mean market capitalisation because the dataset comprised firms from different countries; hence some firms may be disproportionately bigger than others. Fama and French (1996) also used the median. For example, in constructing the emerging African market index, I used three countries – South Africa, Egypt and Morocco – and this makes the new dataset unevenly distributed, as South Africa clearly has the firms with higher market capitalisations.

The stocks were allocated to an independent portfolio based on the book-to-market value groups. This was classed as low (L), medium (M) and high (H) following the classification in

[96] Data source: Reuters Eikon and Datastream

[97] Bartholdy and Peare (2005) find that equal-weighted index, as opposed to value-weighted index provides a better estimate, using CRSP data between 1970 and 1996. They also identify that it does not matter whether dividends are included in the index. Fama and MacBeth (1973) also used an equal-weight portfolio.

[98] Also used by Fama and French. See Table I in Fama and French (2006).

Fama and French (1996), where breakpoints are based on the bottom 30%, the middle 40% and the top 30%. Six sub-portfolios (S/L, S/M, S/H, B/L, B/M, B/H) were formed using the intersection of the two size portfolios and the three value-based portfolios. SMB, as seen in Equation 3.64, is the weekly difference between the average of the returns on the three small-size portfolios $\frac{S}{L}, \frac{S}{M}, \frac{S}{H}$ and the average of the returns on the three big-size portfolios $\frac{B}{L}, \frac{B}{M}, \frac{B}{H}$.

The weekly equal-weighted portfolios are rebalanced at the end of December of year t_{-1} and June of year t and formed every January and July of year t. The returns are calculated every six months from January to June and from July to December of year t.

The value portfolio (HML):[99] Similarly, the HML (high minus low) portfolio mimics the risk factor that relates to the book-to-market equity value:

$$HML = \left(\frac{\Sigma\left(\frac{S}{H}, \frac{B}{H}\right)}{2} \right) - \left(\frac{\Sigma\left(\frac{S}{L}, \frac{B}{L}\right)}{2} \right) \quad (3.65)$$

where i is the HML (high minus low) portfolio for each market i. HML is the weekly difference between the equal-weighted average of the two high book-to-market value portfolios – S/H and B/H; and the equal-weighted average of the returns of the two low book-to-market value portfolios – S/L and B/L. This difference is thus largely free from size effect, focusing instead on the behaviour of the returns of the high and low book-to-market value firms. This equal-weighted portfolio is formed using the book-to-market ratio publicly available six months earlier, i.e. the book-to-market value used for portfolio formation in June is the value available in December of *t – 1*. This is similar to the method in Fama and French (1996). There were no stocks with negative book-to-market values; hence no stock was excluded based on negative values when calculating the breakpoints.

The momentum portfolio (UMD):[100] The UMD (up minus down) portfolio mimics the risk factor that relates to the momentum of the equity of a firm. The momentum portfolio uses Carhart's (1997) four-factor model, which applies a momentum factor in Jegadeesh and Titman (1993). At the end of the last trading week of every holding period n (n = 6 months), the securities are ranked in descending order on the basis of their mean weekly returns in the past n period. The returns calculations are based on average abnormal returns (AAR), as they cause

[99] Data source: Reuters Eikon and Datastream

[100] Data source: Reuters Eikon and Datastream

the list problem in terms of spurious abnormal average return. Fama (1998) highlights the potential spurious abnormal average return, which becomes statistically significant in cumulative abnormal returns (CARs).

This is because the mean of the CAR increases like N number of periods summed, but the standard error increases like $N^{1/2}$. However, for AAR, the pricing error is constant but the standard error of the AAR decreases like $N^{-1/2}$. Also, Andrikopoulos et al. (2008) highlights that "there is an upward bias in the CARs of securities that are low priced compared to an average benchmark and a downward bias in the CARs of relatively-priced securities". Fama (1998) investigated the buy-and-hold abnormal returns (BHARs) and concluded that the bad-model problem with it is most acute. This is because it multiplies (compounds) an expected-return model problem. Fama (1998) goes on to recommend the use of ARRs or CARs instead of BHARs. Mitchell and Stafford (2000) presents evidence to show that BHARs can give a false impression of the speed of price adjustment. This is because BHARs can grow with the return horizon even when there is no abnormal return after a period.

Furthermore, Barber and Lyon (1997) discuss the BHAR return, but identify that inferences are less problematic in AARs and CARs than in BHAR. However, in their later article, Lyon et al (1999) developed an elaborate technique for correcting some of the inference problems of BHARs, but they acknowledge that their improved methods produce inferences no more reliable than AARs or CARs. This is due to the extreme skewness problem induced by compounding.

Five-quantile (quintile) portfolios are formed that equally weights the stocks contained in the bottom quintile, the penultimate quintile, and so on. This follows the quintile analysis of Chan et al (2004). Rohlerder et al (2010)[101] indicate that the quintile- and decile-based portfolio formation are economically the same.

The "loser" portfolio is represented by the bottom quintile, while the "winner" portfolio is represented by the top quintile. The strategy buys the winner portfolio (up) and sells the loser portfolio (down) and holds the position for a semi-annual period (from January to June and from July to December of year t) before rebalancing. This portfolio formation strategy is slightly different from that in Jegadeesh and Titman (1993), who formed the portfolio based

[101] Rohlerder, Scholz and Wilkens (2011) "Survivorship Bias and Mutual Fund Performance: Relevance, Significance, and Methodical Differences." Review of Finance 15, 441-474

on 10 deciles. This is because of the relatively lower number of stocks in our sample when compared to those used in Jegadeesh and Titman (1993).

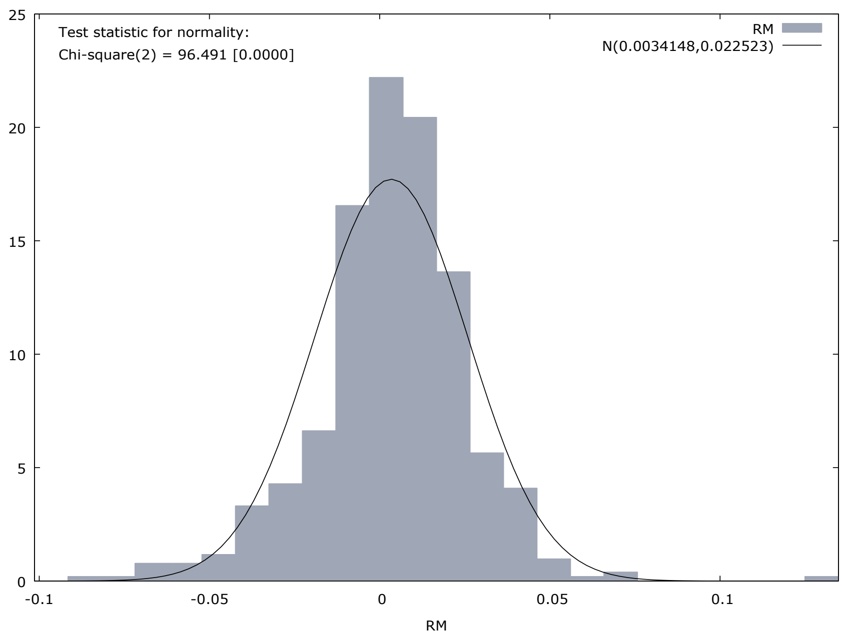
The liquidity portfolio (IMV):[102] The IMV (illiquid minus very liquid) portfolio uses the liquidity construct developed in Lesmond (2005), which measures the trading cost directly using the bid-ask spread identified in Jian (2002). The weekly quoted spread used is defined as

$$Quotedspead_W = \frac{1}{2}\left[\left(\frac{(Ask_W - Bid_W)}{\frac{(Ask_W + Bid_W)}{2}}\right) + \left(\frac{(Ask_{W-1} - Bid_{W-1})}{(Ask_{W-1} + Bid_{W-1})/2}\right)\right] \quad (3.66)$$

A 50th percentile cut-off for illiquid and liquid stocks was used in constructing the portfolio. The portfolios were formed based on weekly average liquidity over the previous n period and held for a further n period before rebalancing.

Skewness and kurtosis: The importance of skewness and kurtosis in the African market has been identified in the literature review and methodological notes. The normality test for the South African market index as shown in Figure 3.6 further demonstrates the non-normality of the data and hence the potential importance of higher moments.

Figure 3.6 Distribution of the returns on the Johannesburg Stock Exchange all share index, Showing test statistic and p-values for normality tests



Test for normality of RM:

[102] Data source: Reuters Eikon and Datastream

Doornik-Hansen test = 96.4914, with p-value 1.11469e-021
Shapiro-Wilk W = 0.966312, with p-value 1.42087e-009
Lilliefors test = 0.0707685, with p-value ~= 0
Jarque-Bera test = 173.867, with p-value 1.75902e-038

The skewness and kurtosis variables are formed using the construct identified in Hwang and Satchell (1999) and Chiao et al. (2003) as follows

$$S_i = \hat{\gamma}_i = \frac{\sum_{t=1}^{-80}[(R_{mt} - \bar{R}_{it})(R_{mt} - \bar{R}_{mt})^2]}{\sum_{t=1}^{-80}(R_{mt} - \bar{R}_{mt})^3} \quad (3.67)$$

$$K_i = \hat{\delta}_i = \frac{\sum_{t=1}^{-80}[(R_{mt} - \bar{R}_{it})(R_{mt} - \bar{R}_{mt})^3]}{\sum_{t=1}^{-80}(R_{mt} - \bar{R}_{mt})^4} \quad (3.68)$$

As highlighted in Chiao et al (2003), the covariance measure within the higher-moment CAPM is denoted as:

$$\hat{\beta}_i = \frac{\sum_{t=1}^{-80}[(R_{mt} - \bar{R}_{it})(R_{mt} - \bar{R}_{mt})]}{\sum_{t=1}^{-80}(R_{mt} - \bar{R}_{mt})^2} \quad (3.69)$$

R_{it} and R_{mt} are the returns of asset i (index returns) and the market, respectively, and $\bar{R}_{it}$ and $\bar{R}_{mt}$ are the expected returns on asset i and the expected market returns, respectively. This skewness and kurtosis measure follows the measures in Kraus and Litzenberger (1976) and Barone-Adesi (1985) designed to avoid the risk of spurious correlation between the systematic risks of the portfolio. To deal with outliers within these two variables, I apply the inverse transformation used in Osborne (2010), to the outliers. As highlighted in Osborne (2002), square roots and logarithmic (e.g. base 10, natural log) scales were not applied in the transformation because some of the outliers were negative. The inverse transformation belongs to power transformations described in Tukey (1957), which merely raises a number to an exponent (power), in this case x^{-1}. Overall, six data points were transformed for the emerging African market index and 13 data points for the frontier African market. These transformations are necessary because, according to Zimmerman (1995), they can improve the results of the analysis.

3.10 Chapter conclusion

This chapter analyses the data problems and evaluates the methodological issues relating to the research questions identified from the literature review (the gaps in the literature), as it applies to the African market. The problems identified relate to the paucity of data and survivorship bias. The correction for these issues were identified in terms of creating an index and correcting for survivorship bias using the CRSP methodology. Other gaps relate to the effects of liquidity on asset pricing in the African market, the role of conditional information in determining excess returns in the African market, the explanatory power of higher-order moments in the African market. I conclude with the following recommendations.

Due to the uniqueness of the African market, the multifactor models, augmented by the liquidity factor, may perform best in explaining the realised returns in the African market. However, to conclude that this is the case, a sequential development approach is recommended, which starts with the Sharpe-Lintner CAPM model, the three and four-factor models of Fama/French and Carhart and their liquidity-augmented variants, respectively.

In forming the liquidity measure, I follow the conclusions in Lesmond (2005) that insist that the most demonstrable indicator of overall liquidity still remains the bid-ask quote; hence this study will employ the bid-ask spread estimate for the liquidity factor. The literature review has also found higher moments to be important in emerging markets, hence the importance of higher moments will also be tested in the African market. This will be done using the higher moments construct of Kraus and Litzenberger (1976), as seen in Chiao et al. (2003).

Given the importance of adjusting for time variation in the African market, the test for structural breaks will follow the three $F-$related test statistics for multiple breaks proposed by Bai and Perron (1998, 2003). For the conditional CAPM model, this study will employ the M-GARCH and GJR-GARCH models and will also model the impact of contagion on conditional correlation and beta. The modelling procedure will be discussed in the methodology section. This chapter also identifies the portfolio formation procedure for the different factors. Using these methodologies, the next chapters will present preliminary results for the South African market, the emerging African market and the frontier African market. Before this, the comprehensive result of the survivorship bias analysis will be evaluated.

3.11 Chapter appendices

Appendix A3.1: Timelines for financial crisis periods and the Arab Spring

Financial crisis timeline[103]

7/9/2008 - The Federal Housing Finance Agency (FHFA) places Fannie Mae and Freddie Mac in government conservatorship. The US Treasury department announces three additional measures to complement the FHFA's decision: 1) preferred stock purchase agreements between the Treasury/FHFA and Fannie Mae and Freddie Mac to ensure the GSE's positive net worth; 2) a new secured lending facility that would be available to Fannie Mae, Freddie Mac and the Federal Home Loan Banks; and 3) a temporary programme to purchase GSE MBS.

15/9/2008 - Lehman Brothers Holdings Incorporated files for Chapter 11 bankruptcy protection.

16/09/2008 - The Federal Reserve Board authorises the Federal Reserve Bank of New York to lend up to $85 billion to the American International Group (AIG) under Section 13(3) of the Federal Reserve Act.

29/10/2008 - The FOMC votes to reduce its target for the federal funds rate 50 basis points to 1.00%. The Federal Reserve Board reduces the primary credit rate 50 basis points to 1.25%.

18/11/2009 - Executives of Ford, General Motors, and Chrysler testify before Congress, requesting access to the Troubled Asset Relief Programme (TARP) for federal loans.

5/1/2009 - The Federal Reserve Bank of New York begins purchasing fixed-rate mortgage-backed securities guaranteed by Fannie Mae, Freddie Mac and Ginnie Mae under a programme first announced on 25 November 2008.

17/2/2009 - President Obama signs into law the American Recovery and Reinvestment Act of 2009, which includes a variety of spending measures and tax cuts intended to promote economic recovery.

11/3/2009 - Freddie Mac announces that it had a net loss of $23.9 billion in the fourth quarter of 2008 and a net loss of $50.1 billion for 2008 as a whole. Further, Freddie Mac announces that its conservator has submitted a request to the US Treasury department for an additional

[103] Source: Federal Reserve Bank of St. Louis https://www.stlouisfed.org/financial-crisis/full-timeline, see also full timeline via this link.

$30.8 billion in funding for the company under the Senior Preferred Stock Purchase Agreement with the Treasury.

7/5/2009 - The Federal Reserve releases the results of the Supervisory Capital Assessment Programme (stress test) of the 19 largest US bank holding companies.

21/5/2009 - Standard and Poor's Ratings Services lowers its outlook on the UK government's debt from stable to negative because of the estimated fiscal cost of supporting the nation's banking system. S&P estimates that this cost could double the government's debt burden to about 100% of GDP by 2013.

Arab Spring timeline[104]

14/1/2011 – Tunisian president Ben Ali resigns.

11/2/2011 – Egyptian president Hosni Mubarak resigns.

20/2/2011 – Libyan president Muammar Gaddafi dies.

15/3/2011 - King Hamad of Bahrain declares a state of emergency and brings in troops from neighbouring Sunni-led Gulf states to restore order.

24/11/2011 – Yemen's president, Ali Abdullah Saleh. agrees to cede power to his vice-president, Abdrabbuh Mansour Hadi.

21/2/2012 - President Assad of Syria presses ahead with a referendum that approves a new constitution that dropped an article giving the ruling Baath Party unique status as the "leader of the state and society".

19/10/2012 - Wissam al-Hassan, a brigadier-general of the Lebanese Internal Security Forces, died along with several others in the 2012 Beirut bombing.

Table A3.2a Breakpoint specification for the test of no break versus a fixed number of breaks for the South African market index

Estimated number of breaks: 5
Method: Bai-Perron tests of 1 to M globally determined breaks
Maximum number of breaks: 5
Breaks: 26/8/2005, 20/4/2007, 29/1/2010, 23/9/2011, 17/5/2013

[104] Source: BBC http://www.bbc.co.uk/news/world-12482291, see also link for full time-line.

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5
UDmax determined breaks:	5
WDmax determined breaks:	5

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical value
1 *	127.7575	127.7575	127.7575	8.58
2 *	80.87399	80.87399	96.10787	7.22
3 *	310.2658	310.2658	446.6578	5.96
4 *	1514.366	1514.366	2603.860	4.99
5 *	1740.356	1740.356	3818.992	3.91

UDMax statistic*	1740.356	UDMax critical value**	8.88
WDMax statistic*	3818.992	WDMax critical value**	9.91

Figure A3.2b Actual, fitted and residual graph for the test of no break versus a fixed number of breaks for the South African market index

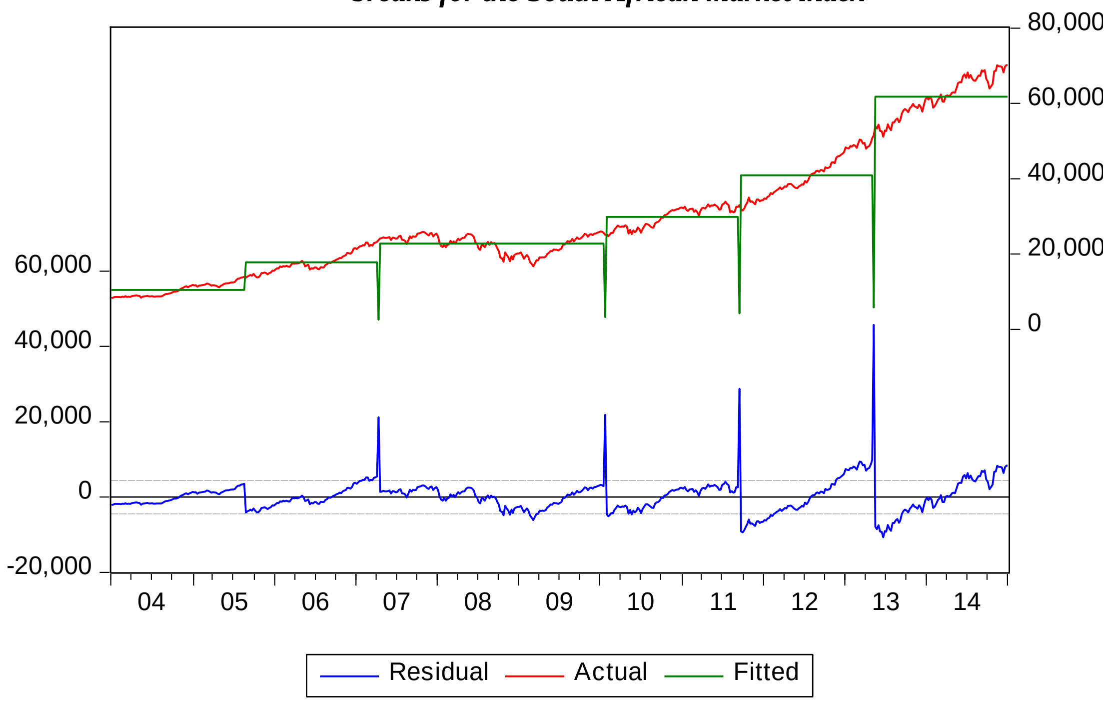


Table A3.3a A test of test of ℓ versus ℓ + 1 breaks for the South African market index

Estimated number of breaks: 3
Method: Bai-Perron tests of L+1 vs. L globally determined breaks
Maximum number of breaks: 5
Breaks: 22/9/2006, 1/10/2010, 4/1/2013

Sequential F-statistic determined breaks:	3
Significant F-statistic largest breaks:	3

Break test	F-statistic	Scaled F-statistic	Critical value**

0 vs. 1 *	127.7575	127.7575	8.58
1 vs. 2 *	736.9474	736.9474	10.13
2 vs. 3 *	230.9048	230.9048	11.14
3 vs. 4	1.750255	1.750255	11.83
4 vs. 5	0.896761	0.896761	12.25

Figure A3.3b Actual, fitted and residual graph for the test of l versus l+1 breaks for the South African market index

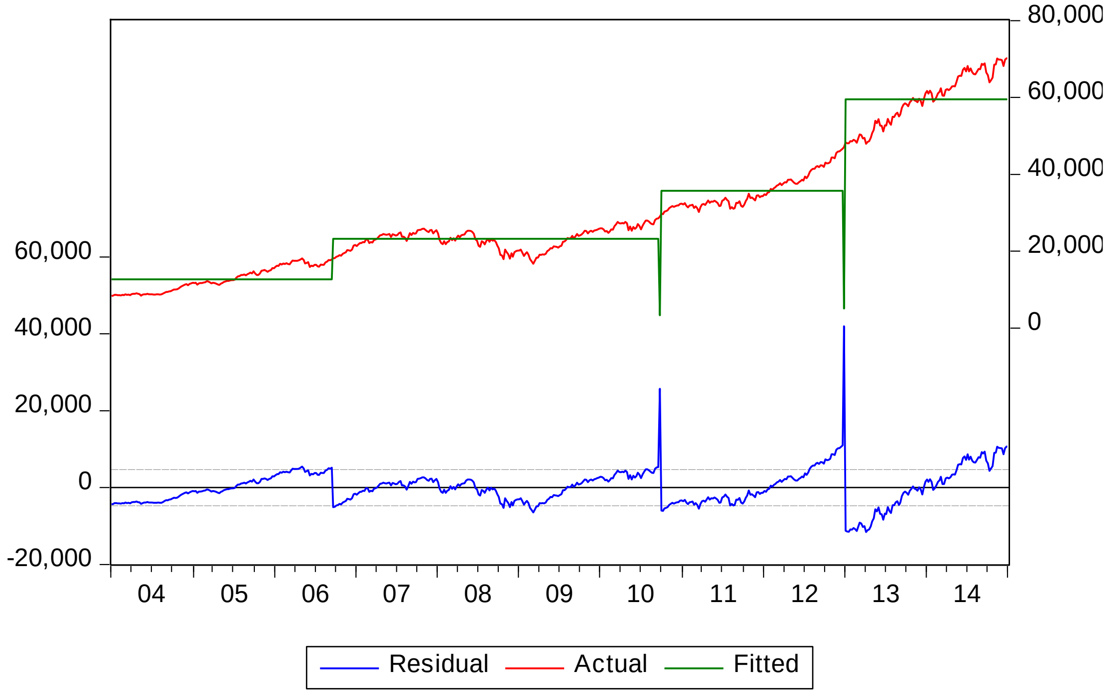


Table A3.37a Breakpoint specification for the test of no break versus a fixed number of breaks for the Egyptian market index

Estimated number of breaks: 3
Method: Bai-Perron tests of 1 to M globally determined breaks
Maximum number of breaks: 5
Breaks: 19/8/2005, 6/4/2007, 21/11/2008

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5
UDmax determined breaks:	3
WDmax determined breaks:	3

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical value
1 *	98.59719	98.59719	98.59719	8.58
2 *	49.07705	49.07705	58.32148	7.22
3 *	1273.202	1273.202	1832.898	5.96
4 *	958.7731	958.7731	1648.552	4.99
5 *	810.5591	810.5591	1778.669	3.91

UDMax statistic*	1273.202	UDMax critical value**	8.88
WDMax statistic*	1832.898	WDMax critical value**	9.91

Figure A3.4b Actual, fitted and residual graph for the test of no break versus a fixed number of breaks for the Egyptian market index

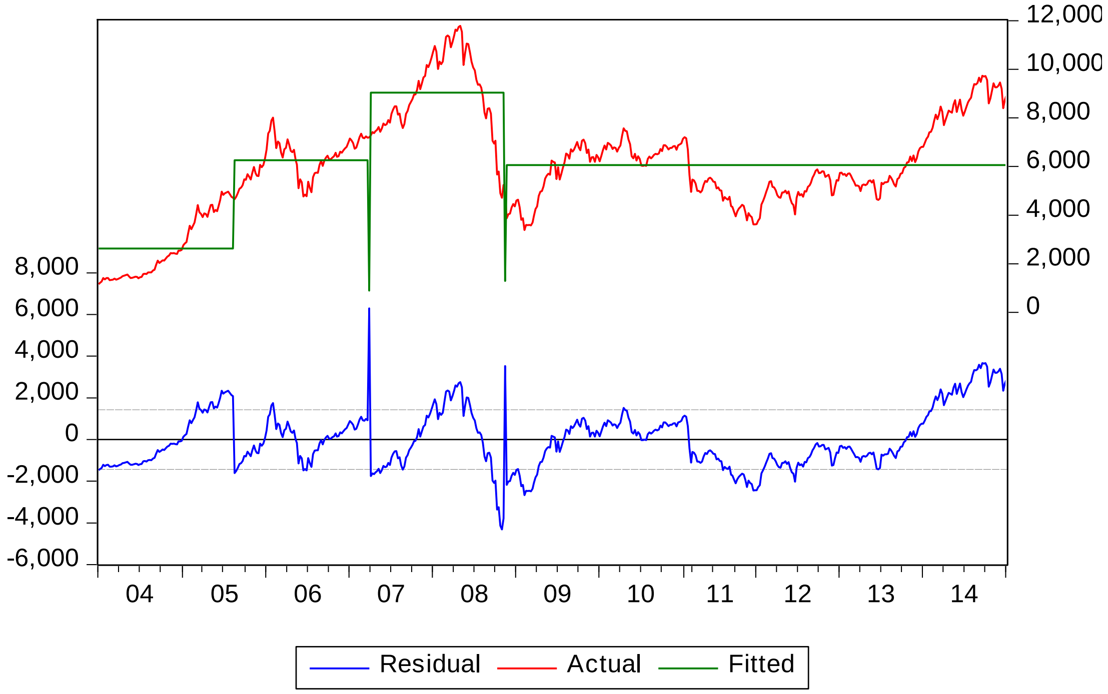


Table A3.5a A test of test of ℓ versus $\ell+1$ breaks for the Egyptian market index

Estimated number of breaks: 1
Method: Bai-Perron tests of L+1 vs. L globally determined breaks
Maximum number of breaks: 5
Break: 19/8/2005

Sequential F-statistic determined breaks: 1
Significant F-statistic largest breaks: 1

Break test	F-statistic	Scaled F-statistic	Critical value**
0 vs. 1 *	98.59719	98.59719	8.58
1 vs. 2	3.291208	3.291208	10.13
2 vs. 3	8.681706	8.681706	11.14
3 vs. 4	8.387214	8.387214	11.83
4 vs. 5	4.135587	4.135587	12.25

Figure A3.5b Actual, fitted and residual graph for the test of l versus l+1 breaks for the Egyptian market index

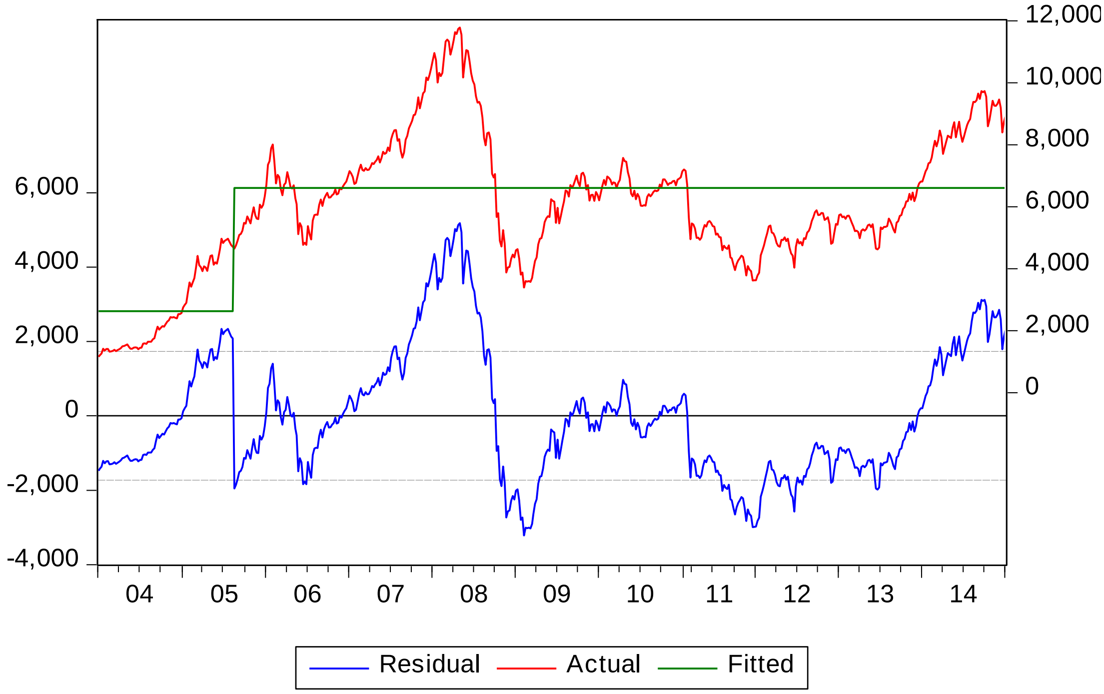


Table A3.6a Breakpoint specification for the test of no break versus a fixed number of breaks for the Moroccan market index

Estimated number of breaks: 4
Method: Bai-Perron tests of 1 to M globally determined breaks
Maximum number of breaks: 5
Breaks: 26/8/2005, 20/4/2007, 12/12/2008, 13/4/2012

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5
UDmax determined breaks:	4
WDmax determined breaks:	5

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical value
1 *	72.88548	72.88548	72.88548	8.58
2 *	109.6630	109.6630	130.3197	7.22
3 *	55.97348	55.97348	80.57927	5.96
4 *	3264.239	3264.239	5612.660	4.99
5 *	2681.023	2681.023	5883.164	3.91

UDMax statistic*	3264.239	UDMax critical value**	8.88
WDMax statistic*	5883.164	WDMax critical value**	9.91

Figure A3.6b Actual, fitted and residual graph for the test of no break versus a fixed number of breaks for the Moroccan market index

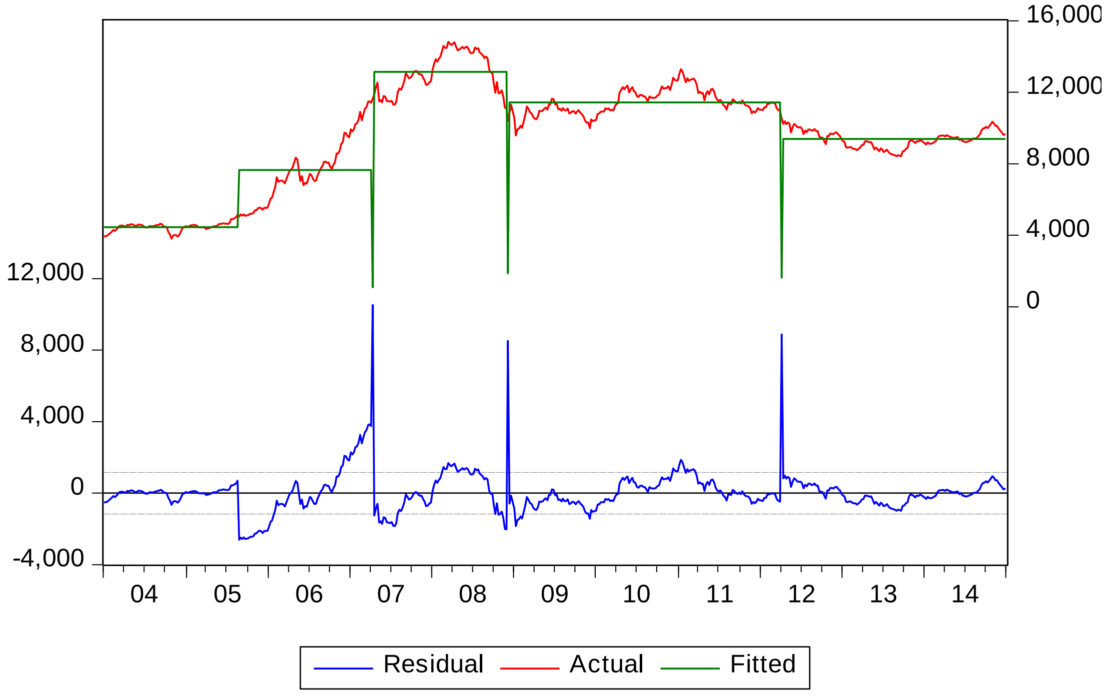


Table A3.7a A test of test of ℓ versus $\ell + 1$ breaks for the Moroccan market index.

Estimated number of breaks: 2
Method: Bai-Perron tests of L+1 vs. L globally determined breaks
Maximum number of breaks: 5
Breaks: 17/11/2006, 6/4/2012

Sequential F-statistic determined breaks: 2
Significant F-statistic largest breaks: 2

Break test	F-statistic	Scaled F-statistic	Critical value**
0 vs. 1 *	72.88548	72.88548	8.58
1 vs. 2 *	56.18281	56.18281	10.13
2 vs. 3	1.919804	1.919804	11.14
3 vs. 4	11.81628	11.81628	11.83
4 vs. 5	7.353054	7.353054	12.25

Figure A3.7b Actual, fitted and residual graph for the test of l versus l+1 breaks for the Moroccan market index

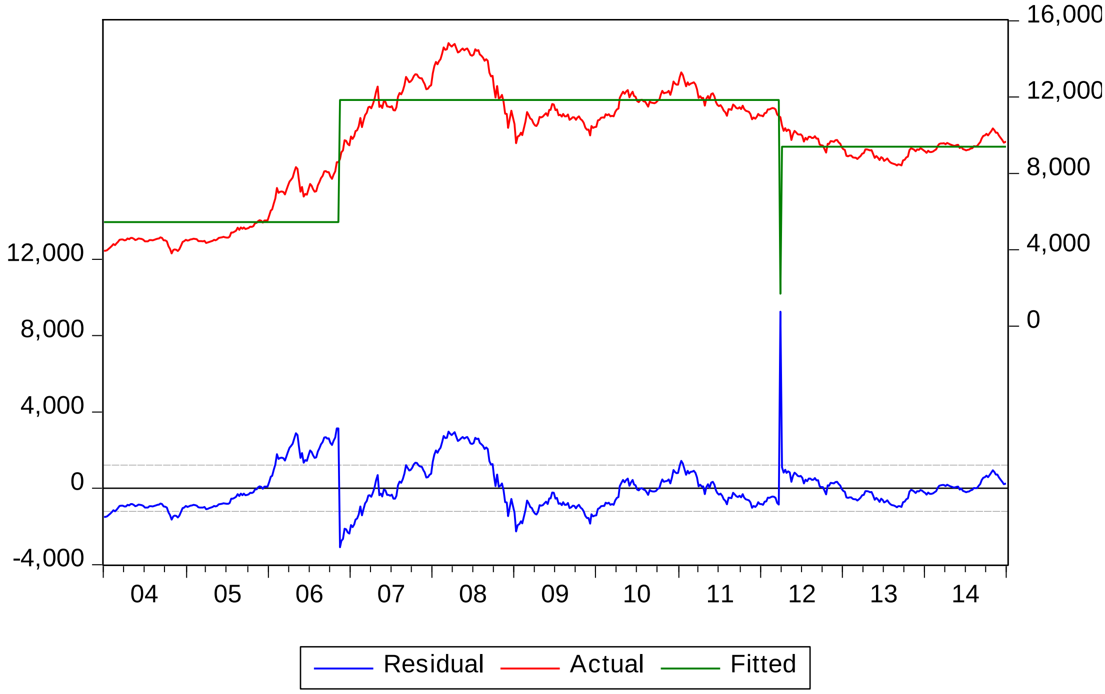


Table A3.8a Breakpoint specification for the test of no break versus a fixed number of breaks for the Botswanan market index

Estimated number of breaks: 5
Method: Bai-Perron tests of 1 to M globally determined breaks
Maximum number of breaks: 5
Breaks: 26/8/2005, 20/4/2007, 12/12/2008, 22/7/2011, 22/3/2013

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5
UDmax determined breaks:	5
WDmax determined breaks:	5

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical value
1 *	132.8815	132.8815	132.8815	8.58
2 *	134.4209	134.4209	159.7412	7.22
3 *	82.22352	82.22352	118.3688	5.96
4 *	75.56034	75.56034	129.9214	4.99
5 *	1269.228	1269.228	2785.160	3.91

UDMax statistic*	1269.228	UDMax critical value**	8.88
WDMax statistic*	2785.160	WDMax critical value**	9.91

Figure A3.8b Actual, fitted and residual graph for the test of no break versus a fixed number of breaks for the Botswanan market index

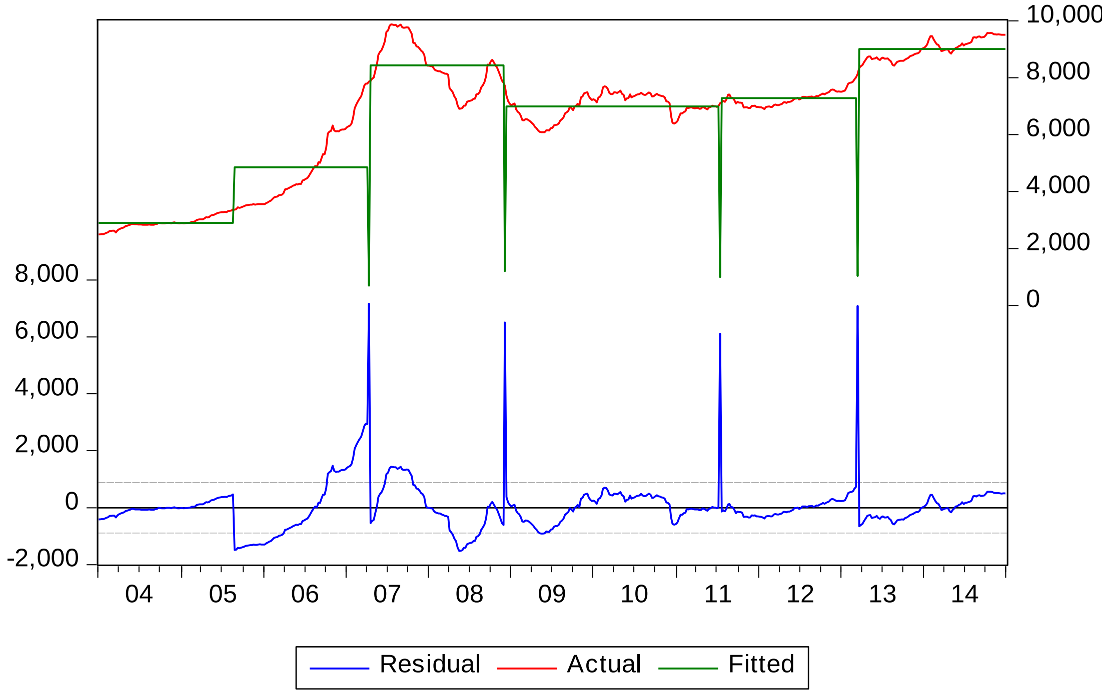


Table A3.9a A test of test of ℓ versus $\ell + 1$ breaks for the Botswanan market index

Estimated number of breaks: 3
Method: Bai-Perron tests of L+1 vs. L globally determined breaks
Maximum number of breaks: 5
Breaks: 13/10/2006, 12/12/2008, 15/3/2013

Sequential F-statistic determined breaks: 3
Significant F-statistic largest breaks: 3

Break test	F-statistic	Scaled F-statistic	Critical value**
0 vs. 1 *	132.8815	132.8815	8.58
1 vs. 2 *	64.82169	64.82169	10.13
2 vs. 3 *	15.47632	15.47632	11.14
3 vs. 4	3.741978	3.741978	11.83
4 vs. 5	0.000000	0.000000	12.25

Figure A3.9b Actual, fitted and residual graph for the test of l versus l+1 breaks for the Botswanan market index

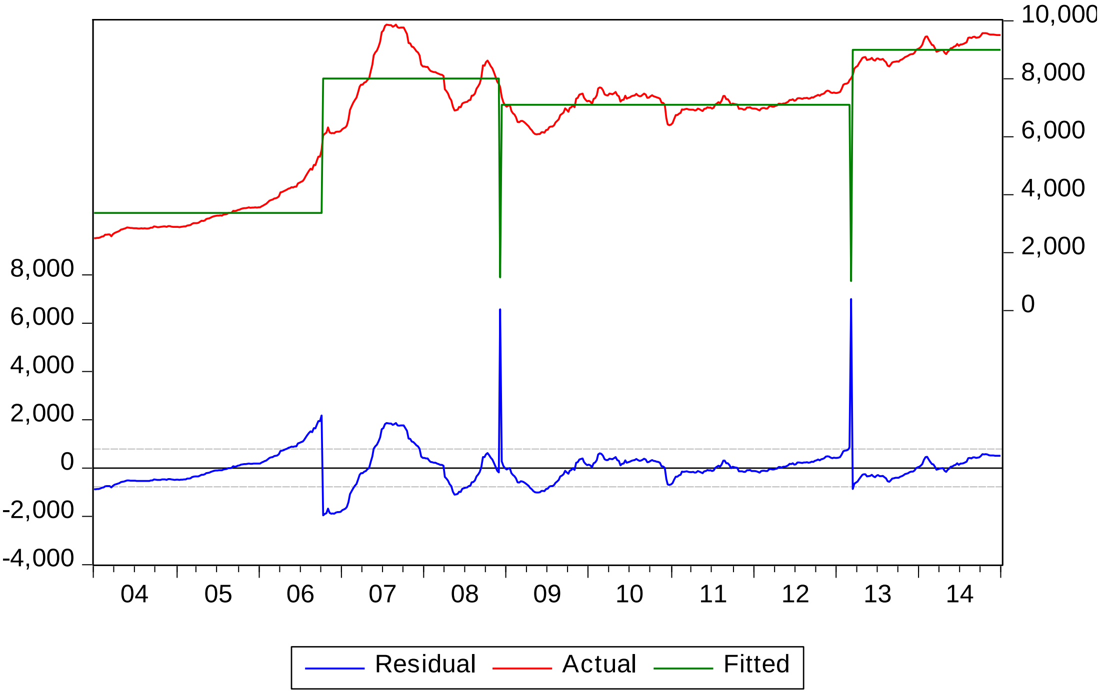


Table A3.380a Breakpoint specification for the test of no break versus a fixed number of breaks for the BRVM - Cote d'Ivoire market index

Estimated number of breaks: 2
Method: Bai-Perron tests of 1 to M globally determined breaks
Maximum number of breaks: 5
Breaks: 13/1/2006, 17/5/2013

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5
UDmax determined breaks:	2
WDmax determined breaks:	5

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical value
1 *	46.92069	46.92069	46.92069	8.58
2 *	179.2227	179.2227	212.9822	7.22
3 *	59.43637	59.43637	85.56443	5.96
4 *	175.8611	175.8611	302.3824	4.99
5 *	177.7579	177.7579	390.0673	3.91

UDMax statistic*	179.2227	UDMax critical value**	8.88
WDMax statistic*	390.0673	WDMax critical value**	9.91

Figure A3.10b Actual, fitted and residual graph for the test of no break versus a fixed number of breaks for the BRVM market index

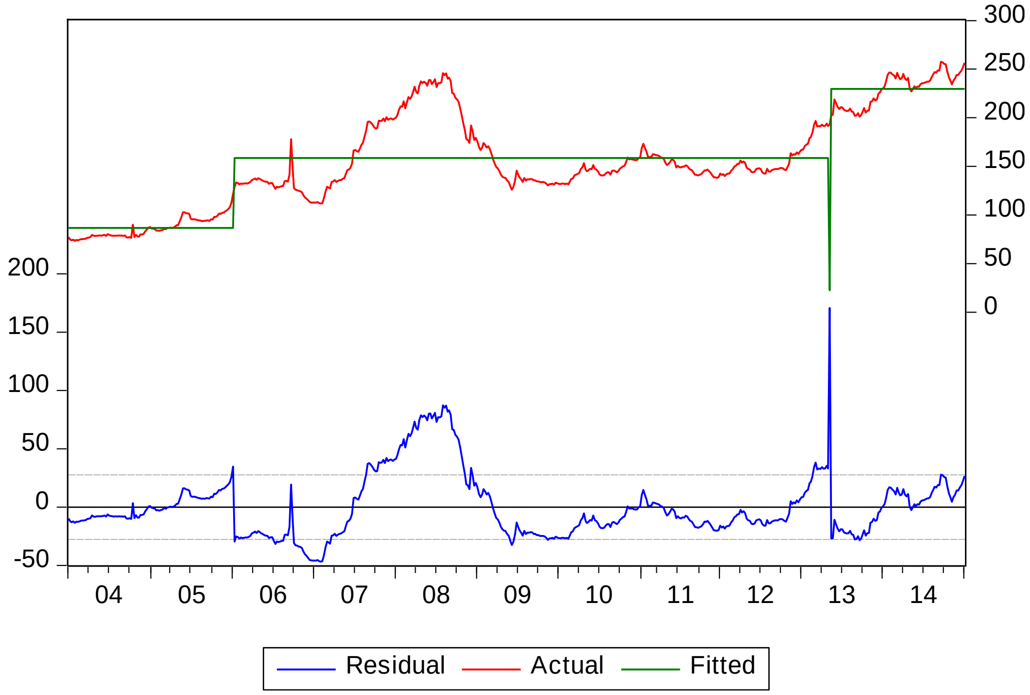


Table A3.11a A test of test of ℓ versus $\ell + 1$ for the BRVM market index.

Estimated number of breaks: 5
Method: Bai-Perron tests of L+1 vs. L globally determined breaks
Maximum number of breaks: 5
Breaks: 2/12/2005, 20/7/2007, 6/3/2009, 22/10/2010, 1/3/2013

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5

Break test	F-statistic	Scaled F-statistic	Critical value**
0 vs. 1 *	46.92069	46.92069	8.58
1 vs. 2 *	52.07231	52.07231	10.13
2 vs. 3 *	19.37104	19.37104	11.14
3 vs. 4 *	70.22438	70.22438	11.83
4 vs. 5 *	15.62443	15.62443	12.25

Figure A3.11b Actual, fitted and residual graph for the test of l versus l+1 breaks for the BRVM market index

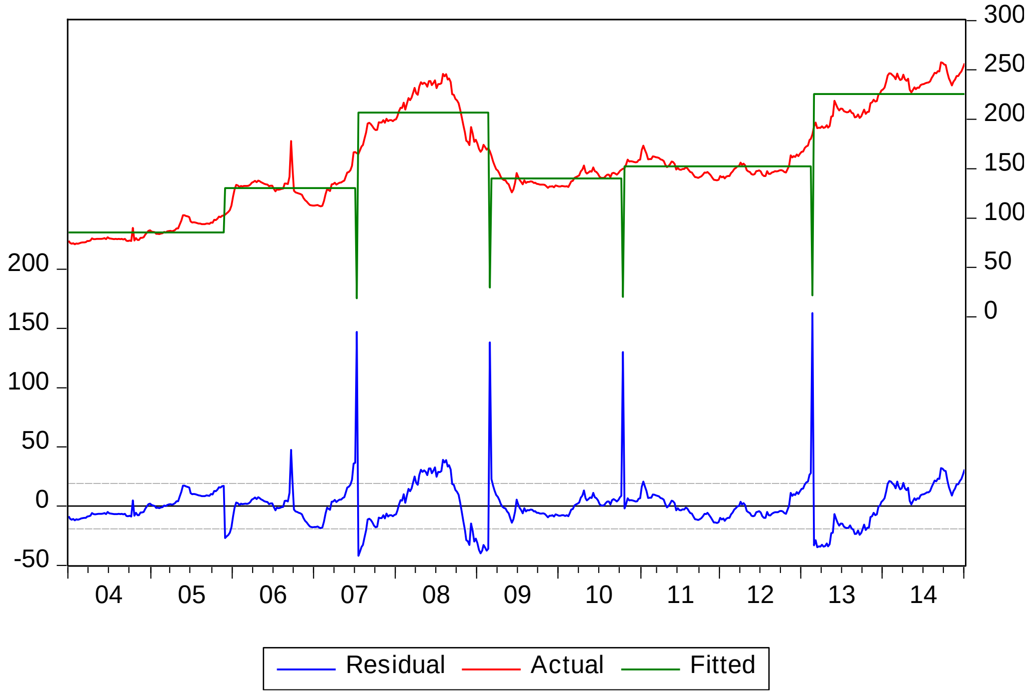


Table A3.392a Breakpoint specification for the test of no break versus a fixed number of breaks for the Kenyan market index

Estimated number of breaks: 3
Method: Bai-Perron tests of 1 to M globally determined breaks
Maximum number of breaks: 5
Breaks: 16/1/2009, 29/1/2010, 29/3/2013

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5
UDmax determined breaks:	3
WDmax determined breaks:	3

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical value
1 *	93.10634	93.10634	93.10634	8.58
2 *	137.3079	137.3079	163.1720	7.22
3 *	186.3725	186.3725	268.3014	5.96
4 *	135.2672	135.2672	232.5837	4.99
5 *	109.1049	109.1049	239.4170	3.91

UDMax statistic*	186.3725	UDMax critical value**	8.88
WDMax statistic*	268.3014	WDMax critical value**	9.91

Figure A3.12b Actual, fitted and residual graph for the test of no break versus a fixed number of breaks for the Kenyan market index

Table A3.13a A test of test of ℓ versus $\ell + 1$ breaks for the Kenyan market index.

Estimated number of breaks: 3
Method: Bai-Perron tests of L+1 vs. L globally determined breaks
Maximum number of breaks: 5
Breaks: 16/1/2009, 29/1/2010, 29/3/2013

Sequential F-statistic determined breaks:	3
Significant F-statistic largest breaks:	5

Break test	F-statistic	Scaled F-statistic	Critical value**
0 vs. 1 *	93.10634	93.10634	8.58
1 vs. 2 *	29.91057	29.91057	10.13
2 vs. 3 *	21.99163	21.99163	11.14
3 vs. 4	4.050629	4.050629	11.83
4 vs. 5 *	37.02445	37.02445	12.25

Figure A3.23b Actual, fitted and residual graph for the test of l versus l+1 breaks for the Kenyan market index

Table A3.404a Breakpoint specification for the test of no break versus a fixed number of breaks for the Nigerian market index

Estimated number of breaks: 5
Method: Bai-Perron tests of 1 to M globally determined breaks
Maximum number of breaks: 5
Breaks: 26/8/2005, 20/4/2007, 12/12/2008, 27/5/2011, 8/1/2013

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5
UDmax determined breaks:	5
WDmax determined breaks:	5

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical value
1 *	22.64809	22.64809	22.64809	8.58
2 *	84.91674	84.91674	100.9121	7.22
3 *	90.27390	90.27390	129.9581	5.96
4 *	79.49843	79.49843	136.6927	4.99
5 *	222.0614	222.0614	487.2856	3.91

UDMax statistic*	222.0614	UDMax critical value**	8.88
WDMax statistic*	487.2856	WDMax critical value**	9.91

Figure A3.34b Actual, fitted and residual graph for the test of no break versus a fixed number of breaks for the Nigerian market index

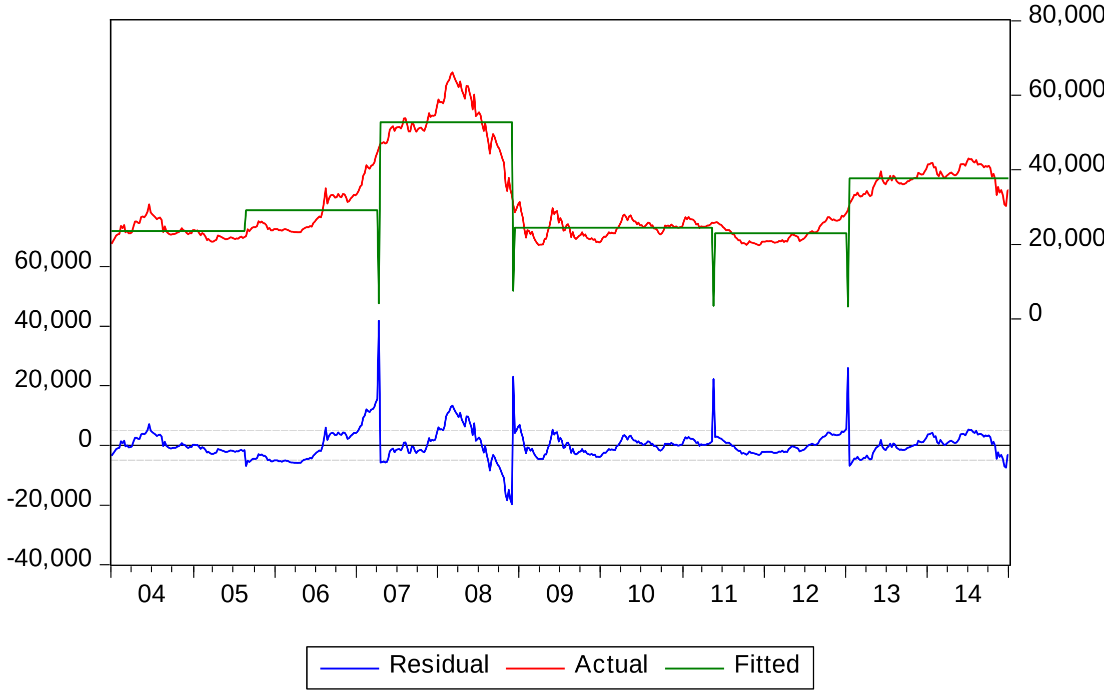


Table A3.15a A test of test of ℓ versus $\ell + 1$ breaks for the Nigerian market index

Estimated number of breaks: 3
Method: Bai-Perron tests of L+1 vs. L globally determined breaks
Maximum number of breaks: 5
Breaks: 9/2/2007, 31/10/2008, 25/1/2013

Sequential F-statistic determined breaks: 3
Significant F-statistic largest breaks: 3

Break test	F-statistic	Scaled F-statistic	Critical value**
0 vs. 1 *	22.64809	22.64809	8.58
1 vs. 2 *	15.12108	15.12108	10.13
2 vs. 3 *	98.79927	98.79927	11.14
3 vs. 4	2.863531	2.863531	11.83
4 vs. 5	0.000000	0.000000	12.25

Figure A3.4b Actual, fitted and residual graph for the test of l versus l+1 breaks for the Nigerian market index

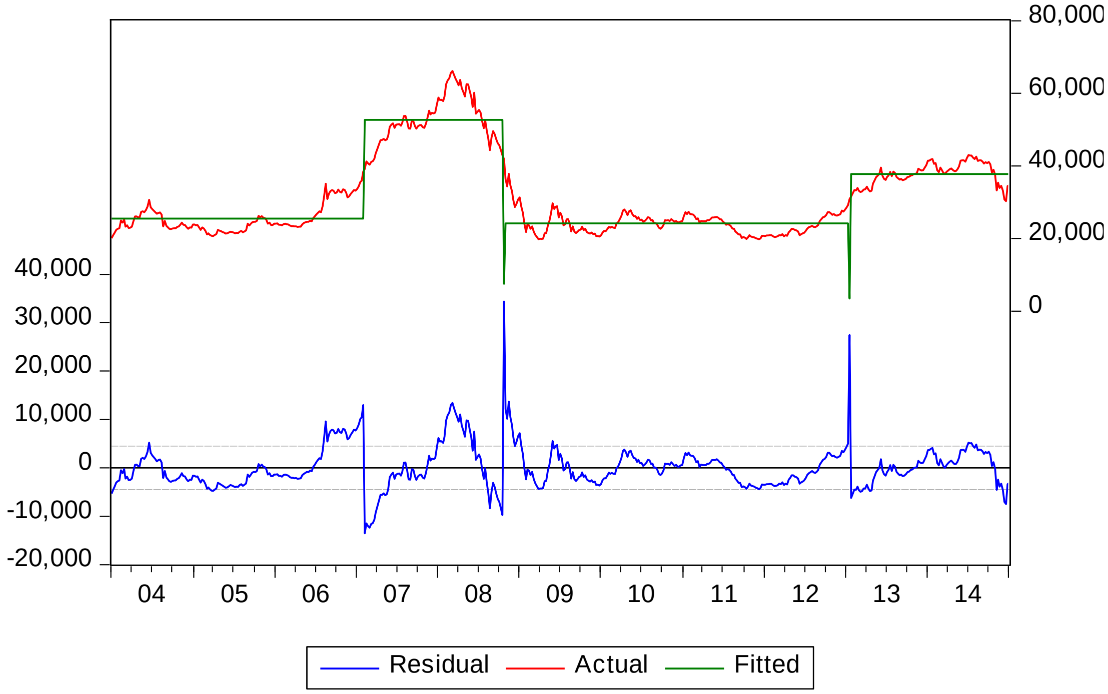


Table 3.16a Breakpoint specification for the test of no break versus a fixed number of breaks for the Tunisian market index

Estimated number of breaks: 5
Method: Bai-Perron tests of 1 to M globally determined breaks
Maximum number of breaks: 5
Breaks: 21/4/2006, 1/2/2008, 18/9/2009, 23/9/2011, 10/5/2013

Sequential F-statistic determined breaks:	5
Significant F-statistic largest breaks:	5
UDmax determined breaks:	5
WDmax determined breaks:	5

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical value
1 *	490.6935	490.6935	490.6935	8.58
2 *	774.0839	774.0839	919.8947	7.22
3 *	831.3221	831.3221	1196.769	5.96
4 *	722.7210	722.7210	1242.675	4.99
5 *	8013.184	8013.184	17583.92	3.91

UDMax statistic*	8013.184	UDMax critical value**	8.88
WDMax statistic*	17583.92	WDMax critical value**	9.91

Figure A3.5b Actual, fitted and residual graph for the test of no break versus a fixed number of breaks for the Tunisian market index

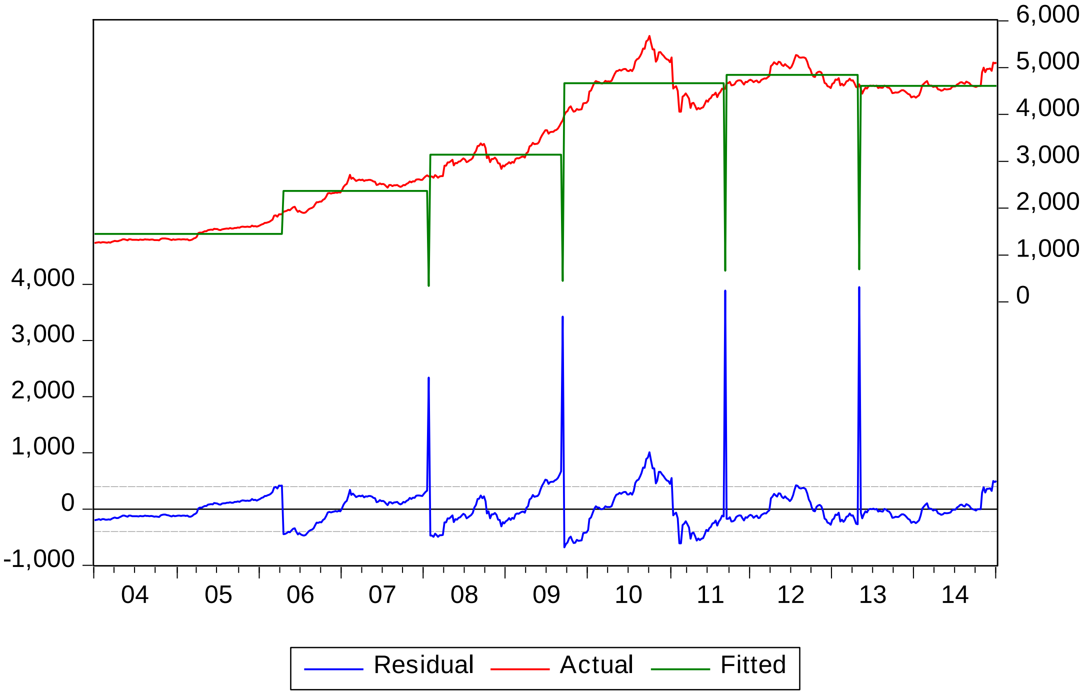


Table 3.17a41 A test of test of ℓ versus $\ell + 1$ breaks for the Tunisian market index

Estimated number of breaks: 2
Method: Bai-Perron tests of L+1 vs. L globally determined breaks
Maximum number of breaks: 5
Breaks: 27/10/2006, 4/9/2009

Sequential F-statistic determined breaks:	2
Significant F-statistic largest breaks:	2

Break test	F-statistic	Scaled F-statistic	Critical value**
0 vs. 1 *	490.6935	490.6935	8.58
1 vs. 2 *	74.95857	74.95857	10.13
2 vs. 3	3.161220	3.161220	11.14
3 vs. 4	3.194017	3.194017	11.83
4 vs. 5	0.000000	0.000000	12.25

Figure A3.67b Actual, fitted and residual graph for the test of l versus l+1 breaks for the Tunisian market index

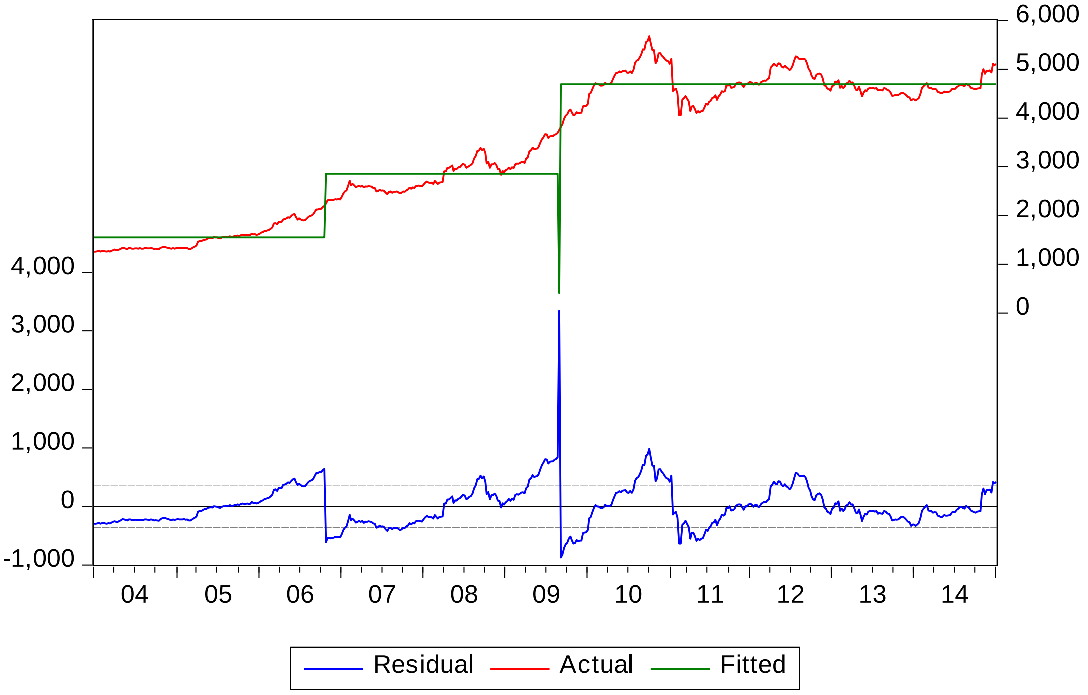


Figure A 3.78 CUSUM test for the returns on the South African market index

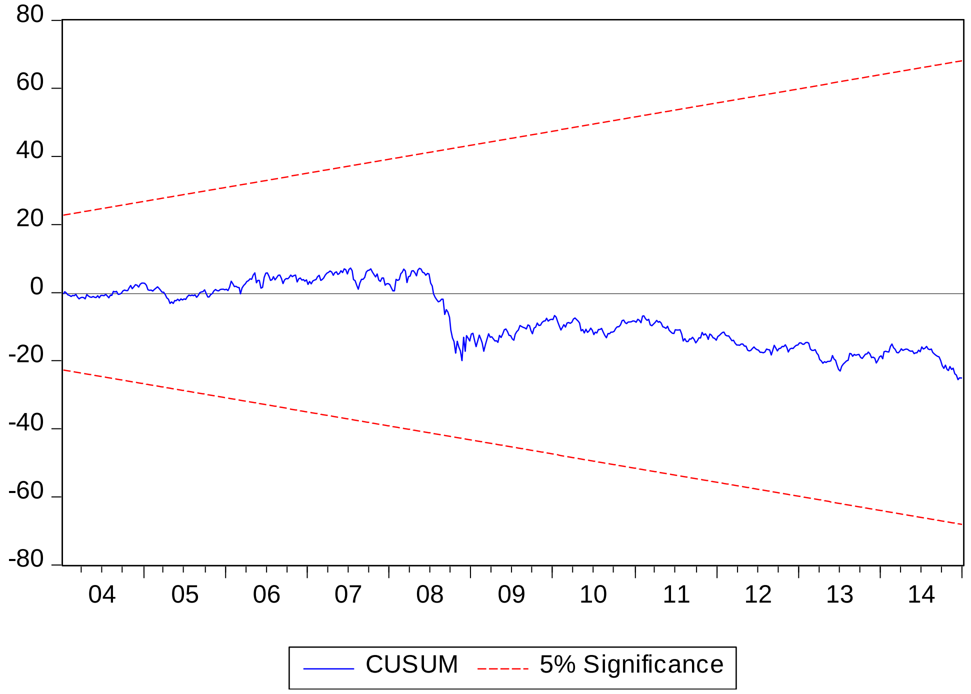


Figure A 3.89 CUSUM of squares test for the returns on the South African market index

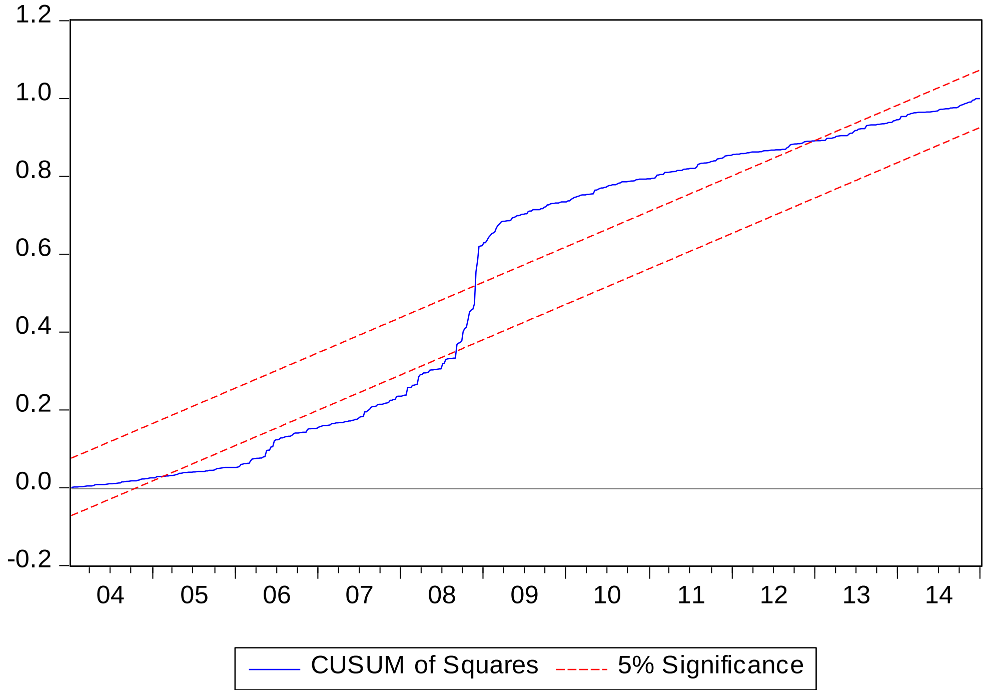


Figure A 3.20 CUSUM test for the returns on the emerging African market index

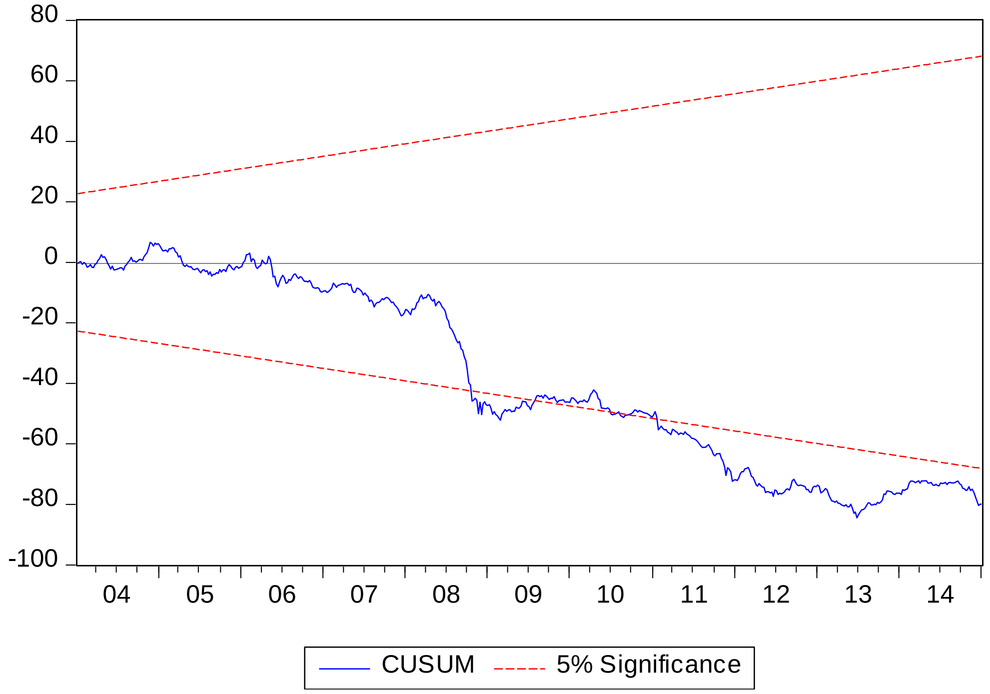


Figure A 3.9 CUSUM of squares test for the returns on the emerging African market index

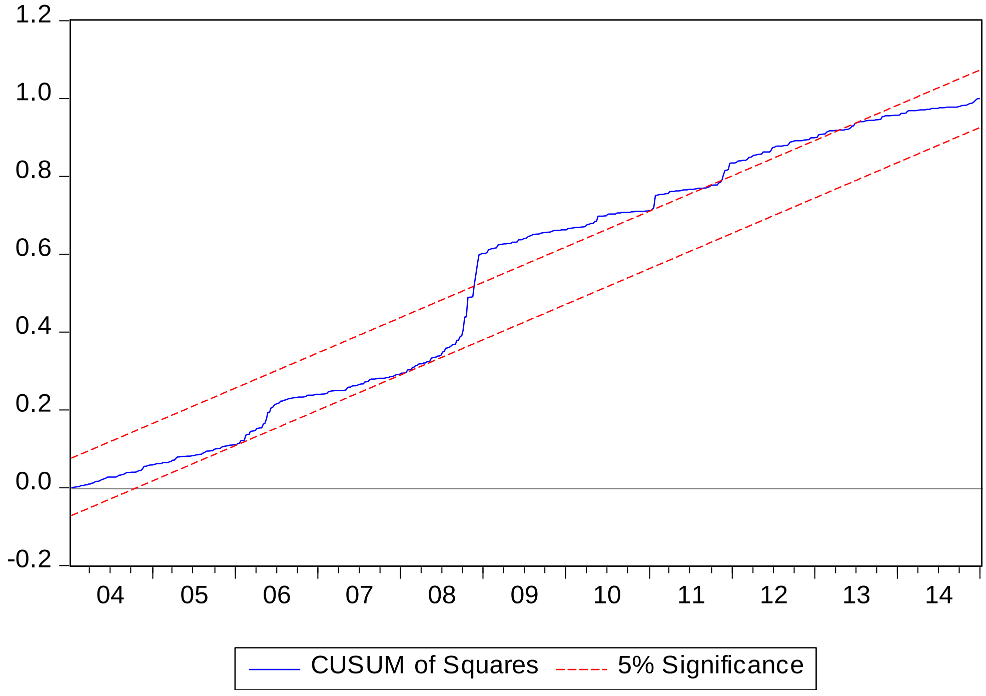


Figure A 3.10 CUSUM test for the returns on the emerging African market excluding South Africa index

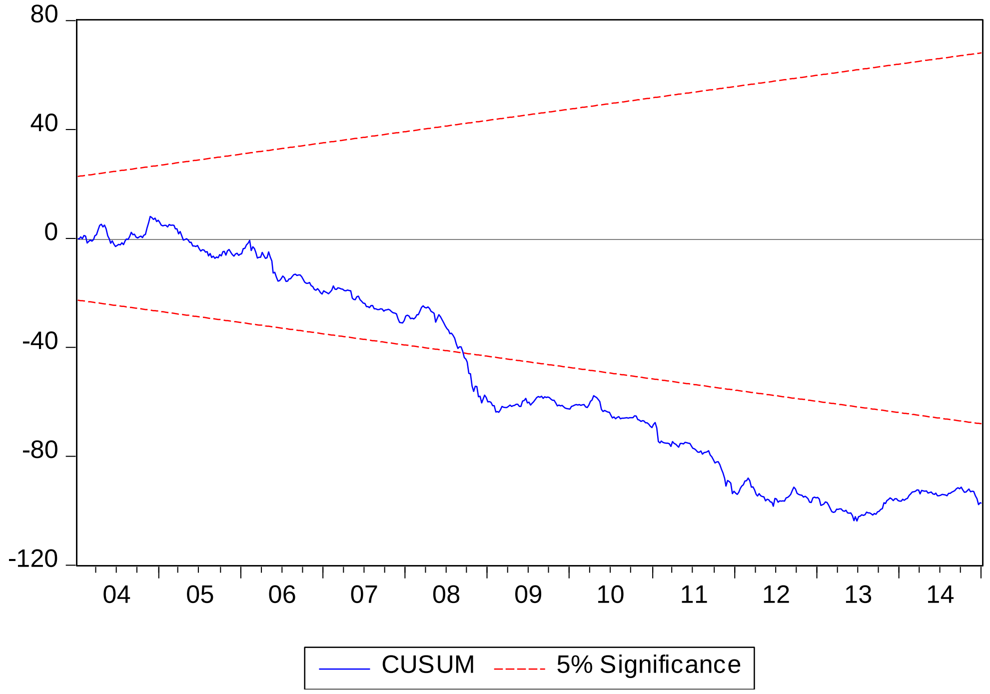


Figure A 3.113 CUSUM of squares test for the returns on the emerging African market excluding South Africa index

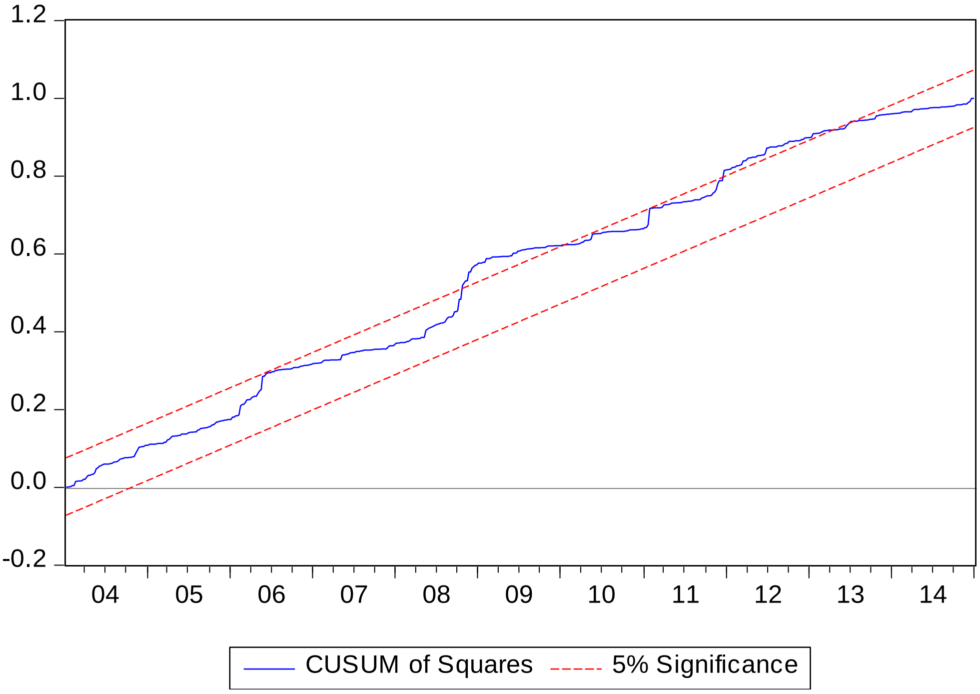


Figure A 3.124 CUSUM test for the returns on the frontier African market index

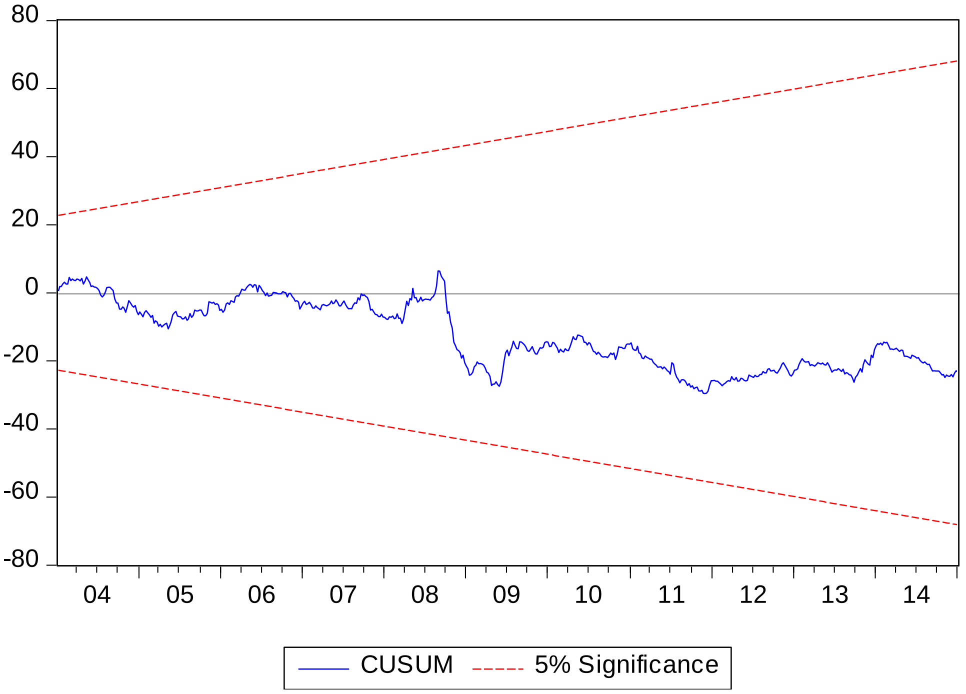
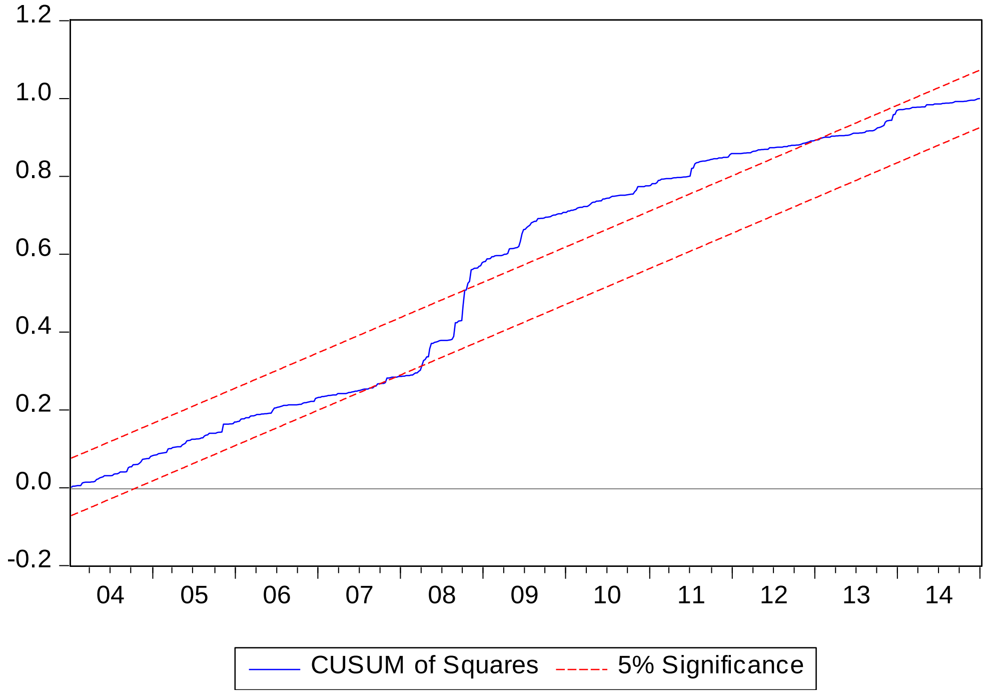


Figure A 3.135 CUSUM of squares test for the returns on the frontier African market index



4 THE EFFECT OF SURVIVORSHIP BIAS ON THE PERFORMANCE OF ASSET-PRICING MODELS IN THE EMERGING AFRICAN MARKET

4.1 Introduction

In the literature review, the importance of eliminating survivorship bias in time-series data was identified. This chapter justifies the elimination of survivorship bias by evaluating survivorship bias in the emerging African market. This chapter will also evaluate the impact of the attrition rate on survivorship bias in these markets. For a robustness check, the outcome is compared to the outcome within the South African market. It is pertinent to note that this chapter is aimed at highlighting the importance of adjusting African market data for survivorship bias; hence I used data on the emerging African market and the South African market from January 2005 to Deccember 2014.

Section 4.2 provides details of the portfolio formation procedure, while Section 4.3 shows the empirical result using the Jensen alpha approach. In Section 4.4, the survivorship bias results for the emerging African market and the frontier African market are discussed, while the relationship between the attrition rate and survivorship bias is established in Section 4.5. Section 4.6 is the chapter conclusion, Section 4.7 the chapter contribution and Section 4.8 the chapter appendices.

4.1.2 Unbiased dataset

The number of firms in the unbiased dataset of the emerging African market (the basic materials sectors of South Africa, Egypt and Morocco) is shown below:

2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
40	47	51	56	63	65	61	60	65	50

Data on some delisted firms have been removed from the database and hence will not be used in this study. The firms are: South Africa – Gold One International (GDOJ.J), Freeworld (FWDJ.J), Eland Platinum (ELDJ.J), Uranium (UUUJ.J); Egypt – HAC (HACCO.CA), AMCC (AMRI.CA).

4.1.3 The biased dataset

The number of firms in the end-of-sample conditioned dataset of the emerging African market (the basic materials sectors of South Africa, Egypt and Morocco) are shown below:

2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
35	35	35	35	35	35	35	35	35	35

4.2 Portfolio formation

The portfolio formation for the asset and market portfolios follows the process identified in Sharpe (1964) and Lintner (1965), while the size and value portfolios follow variants of the formation process in Fama and French (1993). The momentum portfolio follows the formation procedure in Jegadeesh and Titman (1993), while the liquidity portfolio follows the liquidity construct developed in Lesmond (2005). A detailed analysis of the portfolio formation procedure used can be found in Chapter 3.

4.3 Empirical results using the Jensen alpha approach

4.3.1 Emerging African market index *not* sorted for survivorship bias

This study analyses the Sharpe-Lintner CAPM, the Fama-French three-factor model and the Carhart four-factor model, and also includes the liquidity factor within each model.

Variables are defined in the table below.

Variable	**Definition**
α_i	*Jensen alpha term (the constant term)*
β_{iM}	*Beta*
β_{is}	*factor loading on the size factor*
β_{ih}	*factor loading on the value factor*
β_{im}	*factor loading on the momentum factor*
β_{ip}	*factor loading on the liquidity factor*

Table 4.1[105] Time-series regression using equally weighted weekly contemporaneous excess return for the CAPM, three-factor model, four-factor model and their liquidity-augmented variants

Coeff.	CAPM[106]	3-factor model[107]	4-factor model[108]	CAPM + liquidity[109]	3-factor model + liquidity[110]	4-factor model + liquidity[111]
α_i	-0.00129564 (0.000806874)	-0.00144332* (0.000806197)	-0.00145244* (0.000805965)	-0.00150074* (0.000810517)	-0.00154619* (0.000808333)	-0.00155959* (0.000808019)
β_{iM}	0.769343*** (0.0406032)	0.780840*** (0.0407485)	0.779385*** (0.0407538)	0.774618*** (0.0405633)	0.781417*** (0.0407072)	0.779901*** (0.0407061)
β_{is}		0.0831352*** (0.0267805)	0.0757115*** (0.0275093)		0.0705833** (0.0280623)	0.0622787** (0.0288371)
β_{ih}		-0.0786379* (0.0426282)	-0.0627916 (0.0447037)		-0.0862180** (0.0428895)	-0.0697455 (0.0448793)
β_{im}			0.0250166 (0.0213252)			0.0264416 (0.0213198)
β_{ip}				0.0429085** (0.0206150)	0.0324564 (0.0219129)	0.0336407 (0.0219232)
R^2	0.388541	0.400087	0.401552	0.393202	0.402420	0.404054

*, ** and *** indicates statistical significance of the coefficient at the 10%, 5% and 1% levels. Study uses observations 2005-01-07: 2015-01-02[112]. Emerging African market data not sorted for survivorship bias

[105] Heteroscedasticity-corrected using HAC standard errors. Data source – Reuters Eikon.

[106] $R_i - R_f = \alpha_i + \beta_{iM}(R_M) - R_f) + \varepsilon_{it}$

[107] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \varepsilon_{it}$

[108] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \varepsilon_{it}$

[109] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{ip}IMV_t + \varepsilon_{it}$

[110] [110] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{ip}IMV_t + \varepsilon_{it}$

[111] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \varepsilon_{it}$

[112] Descriptive statistics, correlation matrix and the time-series plots of the weekly values of the various factors for the basic materials emerging African index not sorted for survivorship bias are shown in the chapter appendix.

4.3.2 Emerging African market Index *sorted* for survivorship bias

***Table 4.2*[113] *Time-series regression using equally weighted weekly contemporaneous excess return for the CAPM, three-factor model, four-factor model and their liquidity-augmented variants*[114]**

Coeff.	CAPM	3-factor model	4-factor model	CAPM + liquidity	3-factor model + liquidity	4-factor model + liquidity
α_i	−0.00206766 ** (0.000978129)	−0.00201035 ** (0.000971878)	−0.00201280** (0.000971570)	−0.00210284** (0.000989634)	−0.00201197** (0.000972554)	−0.00201522** (0.000971655)
β_{iM}	0.771759 *** (0.0684484)	0.776560*** (0.0648729)	0.774435 *** (0.0643890)	0.780576*** (0.0711353)	0.778630*** (0.0683140)	0.777193*** (0.0678916)
β_{is}		0.0328250 (0.0437052)	0.0321213 (0.0444283)		0.0253645 (0.0431324)	0.0216254 (0.0432183)
β_{ih}		−0.0934450 (0.0644557)	−0.0800838 (0.0638332)		−0.0916887 (0.0667954)	−0.0767385 (0.0656289)
β_{im}			0.0204442 (0.0343857)			0.0217989 (0.0329383)
β_{ip}				0.0268155 (0.0531758)	0.0114386 (0.0593859)	0.0160212 (0.0572467)
R^2	0.399131	0.404177	0.404852	0.393202	0.404262	0.405016

*, ** and *** indicates statistical significance of the coefficient at the 10%, 5% and 1% levels. Study uses observations 2005-01-07: 2015-01-02. Emerging African market data sorted for survivorship bias.

[113] Heteroscedasticity-corrected using HAC standard errors. Data source – Reuters Eikon.
[114] Descriptive statistics, correlation matrix and the time-series plots of the weekly values of the various factors for the basic materials emerging African index sorted for survivorship bias are shown in the chapter appendix

4.3.3 South African basic materials index – *not* sorted for survivorship bias

Table 4.3[115] Time-series regression using equally weighted weekly contemporaneous excess return for the CAPM, three-factor model, four-factor model and their liquidity-augmented variants[116]

Coeff.	CAPM	3-factor model	4-factor model	CAPM + liquidity	3-factor model + liquidity	4-factor model + liquidity
α_i	-0.00110871 (0.00197686)	-0.00106947 (0.00133890)	-0.000447738 (0.00132014)	0.000618477 (0.00176471)	-0.000528182 (0.00130670)	-0.000404742 (0.00135245)
β_{iM}	1.16812*** (0.0920584)	0.880607*** (0.0576336)	0.850363*** (0.0591658)	0.893608*** (0.0821804)	0.816498*** (0.0619216)	0.848551*** (0.0587069)
β_{is}		-0.871156*** (0.0726090)	-0.886990*** (0.0696063)		-0.805907*** (0.0813115)	-0.802354*** (0.0802716)
β_{ih}		-0.130936* (0.0667739)	-0.0671721 (0.0645737)		-0.106899 (0.0703723)	-0.0238405 (0.0601097)
β_{im}			0.0982075* (0.0547490)			0.117811** (0.0507547)
β_{ip}				-0.668190*** (0.0786015)	-0.113758* (0.0682193)	-0.202243*** (0.0609669)
R^2	0.343294	0.632825	0.639003	0.458350	0.404262	0.671013

*, ** and *** indicates statistical significance of the coefficient at the 10%, 5% and 1% levels. Study uses observations 2005-01-07: 2015-01-02. South African market data not sorted for survivorship bias

[115]Heteroscedasticity-corrected using HAC standard errors. Data source – Reuters Eikon.

[116] Descriptive statistics, correlation matrix and the time-series plots of the weekly values of the various factors for the basic materials South African index, sorted for survivorship bias are shown in the chapter appendix

4.3.4 South African basic materials index *sorted* for survivorship bias

Table 4.4[117] Time-series regression using equally weighted weekly contemporaneous excess return for the CAPM, three-factor model, four-factor model and their liquidity-augmented variant[118]

Coeff.	CAPM	3-factor model	4-factor model	CAPM + liquidity	3-factor model + liquidity	4-factor model + liquidity
α_i	−0.00290084** (0.00132269)	−0.00190216 (0.00119628)	−0.00190483 (0.00120075)	−0.00149222* (0.00136406)	−0.00157533 (0.00125385)	−0.00157701 (0.00126148)
β_{iM}	1.07681*** (0.123974)	0.807398*** (0.0815345)	0.807259*** (0.0814176)	0.83919*** (0.105292)	0.782223*** (0.0859341)	0.78214*** (0.0857486)
β_{is}		-0.691088*** (0.0719852)	-0.690659*** (0.0703196)		-0.482328*** (0.0951437)	-0.482083*** (0.0928401)
β_{ih}		0.015861 (0.0850321)	0.0139847 (0.0829662)		0.0338316 (0.0848109)	0.032669 (0.0822062)
β_{im}			0.00300207 (0.0505112)			0.00185722 (0.0474105)
β_{ip}				-0.697963*** (0.0796505)	-0.30421*** (0.106125)	-0.304179*** (0.106339)
R^2	0.366628	0.582827	0.582833	0.548781	0.598517	0.598520

*, ** and *** indicates statistical significance of the coefficient at the 10%, 5% and 1% levels. Study uses observations 2005-01-07: 2015-01-02. South African market data sorted for survivorship bias

[117] Heteroscedasticity-corrected using HAC standard errors. Data source – Reuters Eikon.
[118] Descriptive statistics, correlation matrix and the time-series plots of the weekly values of the various factors for the basic materials South African index sorted for survivorship bias are shown in the chapter appendix

4.4 Survivorship bias results for the emerging African market and the South African market

As stated in Rohleder, Scholz and Wilkens (2011), survivorship bias arises through the measurement of returns of a portfolio that includes only surviving funds. Generally, this will lead to the overestimation of performance. In measuring the survivorship bias, I follow the method in Rohleder, Scholz and Wilkens (2011), which uses the Jensen alpha. For the emerging African market, our analysis showed a survivorship-biased Jensen alpha of −12.96 basis points per week using the Sharpe-Lintner CAPM. The corresponding unbiased Jensen alpha in the analysis was −20.68 basis points per week. The difference of 7.72 basis points per week (402.55[119] basis points per year) is usually referred to as survivorship bias.

Using the Fama-French three-factor model the analysis showed a biased Jensen alpha of -14.43 basis point per week while the corresponding unbiased dataset showed a Jensen alpha of -20.10 basis point per week. The difference of 5.67 basis points per week (295.67 basis point per year) is the survivorship bias. Using the Carhart four-factor model, the analysis showed a biased Jensen alpha of -14.52 basis point per week while the corresponding unbiased data showed Jensen alpha of -20.13 basis point per week. The difference of 5.60 basis point per week (292.19 basis point per year) is the survivorship bias.

When the Sharpe-Lintner CAPM is augmented by the liquidity factor, the analysis showed a biased Jensen alpha of −15.01 basis points per week, while the corresponding unbiased Jensen alpha was −21.03 basis points per week. The difference of 6.02 basis points per week (313.95 basis points per year) is the survivorship bias. This is lower than the 7.72 basis points per week for the unaugmented Sharpe-Lintner CAPM. For the liquidity-augmented three-factor model, the analysis showed a biased Jensen alpha of −15.46 basis points per week, while the corresponding unbiased Jensen alpha was −20.12 basis points per week. This is a difference of 4.66 basis points per week (242.87 basis points per year), which is less than the 5.67 basis points per week reported for the unaugmented three-factor model.

The liquidity-augmented four-factor model showed a biased Jensen alpha of −15.60 basis points per week, while the corresponding unbiased Jensen alpha was −20.15 basis points per week. The difference of 4.56 basis points per week (237.59 basis points per year) is the survivorship bias, which is less than the 5.60 basis points for the unaugmented Carhart model.

[119] 52.1429 weeks in a year.

The average survivorship bias for all the models is 297.47 basis points per year for the basic materials index of the emerging African market between January 2005 and December 2014. This is higher than the 157 basis points per year reported in Rohleder, Scholz and Wilkens (2011), using the US domestic equity mutual fund market from 1993 through 2006. Deaves (2004) also reports a lower value in the Canadian market. They find the average difference between alphas of surviving funds and those that cease existence by the end, using unweighted average alphas, ranges from 232 to 271 basis points. Grinblatt and Titman (1989) report results that are lower than those in Deaves (2004).

For the South African market only, our analysis showed survivorship-biased Jensen alpha of −11.09 basis points per week using the Sharpe-Lintner CAPM. The corresponding unbiased Jensen alpha in the analysis was −29.01 basis points per week. The difference of 17.92 basis points per week (934.47 basis points per year) is usually referred to as survivorship bias**.**

Using the Fama-French three-factor model, the analysis showed a biased Jensen alpha of −10.70 basis points per week while the corresponding unbiased dataset showed a Jensen alpha of −19.02 basis points per week. The difference of 8.33 basis points per week (434.19 basis points per year) is the survivorship bias. Using the Carhart four-factor model, the analysis showed a biased Jensen alpha of -4.48 basis point per week while the corresponding unbiased data showed Jensen alpha of −19.05 basis points per week. The difference of 14.57 basis points per week (759.77 basis points per year) is the survivorship bias.

When the Sharpe-Lintner CAPM is augmented by the liquidity factor, the analysis for the South African market showed a biased Jensen alpha of 6.9 basis points per week, while the corresponding unbiased Jensen alpha was −14.92 basis points per week. The difference of 21.11 basis points per week (1100.59 basis points per year) is the survivorship bias. This is higher than the 17.92 basis points per week for the unaugmented Sharpe-Lintner CAPM. For the liquidity-augmented three-factor model, the analysis showed a biased Jensen alpha of −5.28 basis points per week, while the corresponding unbiased Jensen alpha was −15.75 basis points per week. This is a difference of 10.47 basis points per week (546.01 basis points per year), which is higher than the 8.33 basis points per week reported for the unaugmented three-factor model.

The liquidity-augmented four-factor model showed a biased Jensen alpha of −4.05 basis points per week, while the corresponding unbiased Jensen alpha was −15.77 basis points per week.

The difference of 11.72 basis points per week (611.25 basis points per year) is the survivorship bias, which is less than the 15.57 basis points for the unaugmented Carhart model.

The average survivorship bias of all the models is 731.05 basis points per year for the basic materials index of the South African market between January 2005 and December 2014. This is quite high compared with the findings in the literature as seen in Grinblatt and Titman (1989), Deaves (2004) and Rohleder, Scholz and Wilkens (2011). A significant finding within the analysis is the difference between the emerging African market and the South African market. I found that survivorship bias for the South African basic materials index was higher than that of the emerging African market basic materials index.

This can be explained by the attrition rate of stocks on the index as highlighted in the chapter appendix – Tables A4.9, A4.10 and A4.11, where the average attrition rate on the South African basic materials index is 12%, compared with 12% and 11% for Egypt and Morocco, respectively. This is supported by Liang (2000), who demonstrates that a low attrition rate leads to low survivorship bias.

Some other authors estimated survivorship bias using the difference between the mean returns of all stocks and surviving stocks, as seen in Eling (2008). Using this method, Brown, Goetzman and Ibbotsen (1999), Liang (2000, 2001) and Brown, Goetzman and Park (2001) found survivorship bias that ranged from 60 to 360 basis points per year. Amin and Kat (2003) also found survivorship bias of 200 basis points per year. However, Pawley (2006) indicates that these differences are mainly methodological and data-related. Using this method, the mean returns for the biased emerging African market dataset (surviving stocks) is 16.55 basis points per week and the mean for the unbiased variant (all stocks) is 9.66 basis points per week, as shown in Table 4.5.

Table 4.5[120] Descriptive statistics of the returns on the biased emerging African market index (surviving stocks) and the unbiased emerging African market index (all stocks as at when on the index)

	Mean	Median	Minimum	Maximum	Std dev.
Biased South Africa	0.0014	0.0032	−0.1373	0.1441	0.0329
Unbiased South Africa	0.0003	0.0016	−0.1421	0.1149	0.0292

[120] Data source – Reuters Eikon.

The difference of 6.89 basis points per week (359[121] basis points per year) is the survivorship bias for the basic materials index of the emerging African market from January 2005 to December 2014, which is rather high when compared to previous studies.

For the South African market, the mean returns for the biased dataset (surviving stocks) is 13.67 basis points per week and the mean for the unbiased dataset (all stocks) is 3.24 basis points per week, as shown in Table 4.6.

Table 4.6[122] Descriptive statistics of the returns on the biased South African basic materials index (surviving stocks) and the unbiased variant (includes all stocks as at when on the index).

	Mean	Median	Minimum	Maximum	Std dev.
Biased emerging Africa	0.001655	0.002805	−0.13208	0.097097	0.025763
Unbiased emerging Africa	0.000966	0.002545	−0.15812	0.080602	0.024846

The difference of 10.44 basis points per week (544[123] basis points per year) is the survivorship bias for the South African basic materials index from January 2005 to December 2014, which is rather high when compared to previous studies and to the emerging African market.

4.5 Attrition rate and survivorship bias

Most of the studies on attrition rate and survivorship bias are within the developed markets and some emerging markets. In their study of US hedge funds, Liang (2000) demonstrates that a low attrition rate leads to low survivorship bias if poor performance is the reason for firm disappearance. Bali et al. (2014) found the annual attrition rate was 8.2% between 1994 and 2007, but this number changed enormously to 19.6% between 2008 and 2011. Bali et al. (2014) reveal that this increase was as a result of the severity of the financial crisis. Bali et al. (2012) found similar results.

[121] 52.1429 weeks in a year.
[122] Data source – Reuters Eikon.
[123] 52.1429 weeks in a year.

Table 4.7 Attrition rate for the basic materials indices for the emerging African market

Emerging African markets' basic materials index attrition rate					
Year	Year start	Entry	Exit	Year end	Attrition rate
2005	35	0	1	34	3%
2006	34	25	11	48	32%
2007	48	4	4	48	8%
2008	48	3	2	49	4%
2009	49	18	2	65	4%
2010	65	7	9	63	14%
2011	63	4	9	58	14%
2012	64	1	11	54	17%
2013	54	4	7	51	13%
2014	51	7	11	47	22%
Average attrition rate					13%

**Attrition rate is calculated as the percentage of firms removed from the index to the number of firms that were on the index at the beginning of the year. The attrition rates for individual countries within the emerging African market are reported in the appendix – see Tables A4.9, A4.10 and A4.11.

From Table 4.7, the attrition rate of 13% in our sample can be referred to as high when compared to other studies. Carpenter and Lynch (1999) found an attrition rate of 3.6% in their study of the US market. They identified that attrition increases each percentile's average performance in the evaluation period. Brown et al. (1992) identified an attrition rate ranging from 2.6% in 1985 to 8.5% in 1977, with an average of 4.8%. They also highlight that this is close to the 5% attrition rate found in Grinblatt and Titman (1989). Brown et al. (1992) hypothesise that as the number of firms increases through time, the attrition rate would also be expected to increase. In their study of mutual fund performance, Rohleder et al. (2010) report a growth in relative annual fund disappearance of 8.64%, from 5.25% between 1993 and 2006. Carhart (1997) also reports an attrition rate of 3.6% between 1962 and 1995.

Studies on the attrition rate of African financial markets are very rare, with the only study found being the study by Pawley (2006), who found the attrition rate of South African unit trusts to be 5.23% per year. This study also found that the attrition rate increases with time, reporting an attrition rate of 52.59% at the 20-year mark. Pawley (2006) also identifies that attrition rates are increasing significantly over time, hence suggesting a lower future survival rate. This is consistent with the findings within the analysis for this research as seen in Table 4.7.

4.6 Chapter conclusion

The returns overestimation problem that results from survivorship bias arises due to the formation of portfolios that include only surviving stocks, particularly based on end-of-sample conditioning. In analysing the degree of survivorship bias in the emerging African market, we observe a survivorship bias of 402.55, 295.67 and 292.19 basis points per year for the Sharpe-Lintner CAPM, Fama-French model and the Carhart model, respectively, using the Jensen alpha term. For the liquidity-augmented models, I found survivorship bias of 313.95, 242.87 and 237.59 basis points per year respectively, with an overall mean survivorship bias of 297.47 basis points per year. Using the mean returns of the biased and unbiased datasets, I found survivorship bias of 359 basis points per year. These are quite high when compared with findings in other studies. These can be explained by the relatively high attrition rate of firms on the basic materials emerging African index.

The attrition rate for the basic materials emerging African index is 12%, which is quite high when compared with findings in the literature. However, previous studies offer some explanation for this, with Brown et al. (1992) hypothesising that as the number of firms increases through time, the attrition rate would also be expected to increase. This is also supported by Pawley (2006).

For the basic materials South African index, I observe a survivorship bias of 934.47, 434.19 and 759.77 basis points per year for the Sharpe-Lintner CAPM, Fama-French model and the Carhart model, respectively, using the Jensen alpha term. For the liquidity-augmented models, I found survivorship bias of 1100.59, 546.01 and 611.25 basis points per year, respectively, with an overall mean survivorship bias of 731.05 basis points per year. Using the mean returns of the biased and unbiased datasets, I found survivorship bias of 544 basis points per year. This is quite high when compared with findings in the literature and also high when compared to the emerging African market. This can also be explained by the higher attrition rate of the South African market of 12%, compared to attrition rates of 11% for the Moroccan market, although similar to the finding in the Egyptian market.

4.7 Chapter contribution

The thesis makes a contribution to the African CAPM literature by taking into consideration the impact of survivorship bias on the modelling of stock-market returns. To the best of my knowledge, this has not been undertaken comprehensively before in the emerging African market context.

Grinblatt and Titman (1989) was one of the first to identify in a US context that failure to take survivorship bias into consideration would bias the econometric modelling of stock returns. The findings in this study indicate that this issue is even more important in an African context.

The thesis finds average survivorship bias of 297.47 basis points per year for the basic materials emerging African index stocks (January 2005 to December 2014), and 731.05 basis points per year for the basic materials South African index stocks, over the same period, using the Jensen alpha methodology highlighted in Rohleder, Scholz and Wilkens (2011). This can be compared with the 157 basis points per year reported in Rohleder, Scholz and Wilkens (2011), using data from the US domestic equity mutual fund market (1993 to 2006), with lower values reported in other developed markets (Deaves, 2004).

Using the mean difference methodology, as identified in Eling (2008), I find survivorship bias of 359 basis points per year for the basic materials emerging African index stocks (January 2005 to December 2014). For the basic materials South African index, the corresponding survivorship bias was 544 basis points per year, during the same time period. These values are also high when compared with previous studies that applied the same methodology, as seen in Brown, Goetzman and Park (2001) and Amin and Kat (2003), who find survivorship bias of 60 to 360 basis points per year and 200 basis points per year, respectively, both in the US market.

Attrition rates are directly related to survivorship bias; a low attrition rate will lead to low survivorship bias, as identified in Liang (2000). This study finds the average attrition rate in the emerging African market to be much higher (13%) than those found in US studies (for example, Carpenter and Lynch, 1999 found an attrition rate of 3.6%). My research therefore calls into question previous studies on asset pricing in African markets that do not adjust for survivorship bias.

4.8 Chapter appendices

Appendix 4.1: Descriptive statistics of the emerging African market not sorted for survivorship bias and time-series plot of the factors

The summary statistics for the excess market returns portfolio, size portfolio, value portfolio, momentum portfolio and liquidity portfolio respectively are shown in Table A4.1

Table A 4.1: Summary statistics for the emerging Africa market not sorted for survivorship bias

Summary statistics, using the observations from 2005-01-07 - 2015-01-02								
Variable	Mean	Median	Minimum	Maximum	Std dev.	CV	Skewness	Ex. kurtosis
MKT	0.0031	0.0046	−0.1140	0.0726	0.0196	6.2532	−1.0162	4.0794
SMB	0.0025	0.0040	−0.1165	0.1029	0.0308	12.1285	−0.2587	1.1020
HML	0.0013	0.0010	−0.0658	0.0702	0.0193	15.1684	0.0442	1.3715
UMD	0.0005	0.0029	−0.1529	0.1523	0.0394	79.1660	−0.2746	1.9654
IMV	0.0044	0.0030	−0.1208	0.2296	0.0386	8.7951	1.1896	5.1554

Table A 4.2 Correlation coefficient for the emerging Africa market not sorted for survivorship bias

MKT	SMB	HML	UMD	IMV	
1	−0.1400	−0.0879	0.0237	−0.0625	MKT
	1	0.2619	0.1472	0.3404	SMB
		1	−0.2515	0.1981	HML
			1	−0.0223	UMD
				1	IMV

Table A4.2 shows the correlations between the explanatory variables. It does not detect any overly high value of the correlation coefficients that may give rise to any concerns of multicollinearity problem.

Figures A4.1, A4.2, A4.3, A4.4 and A4.5 plot the weekly value of the market factor (MKT), the size factor (SMB), the value factor (HML), the momentum factor (UML) and the liquidity factor (IMV), respectively.

Figure A 4.1 Weekly value of the market factor (MKT)

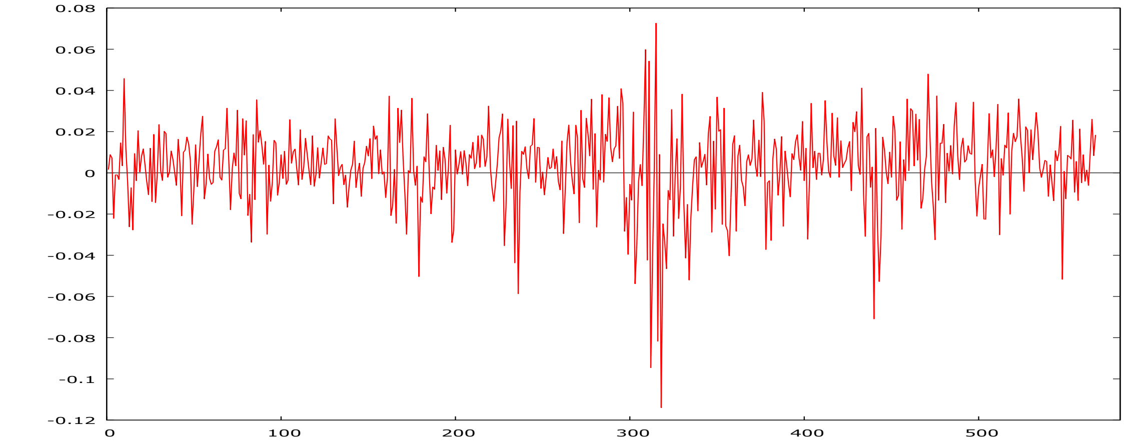


Figure A 4.2 Weekly value of the size factor (SMB)

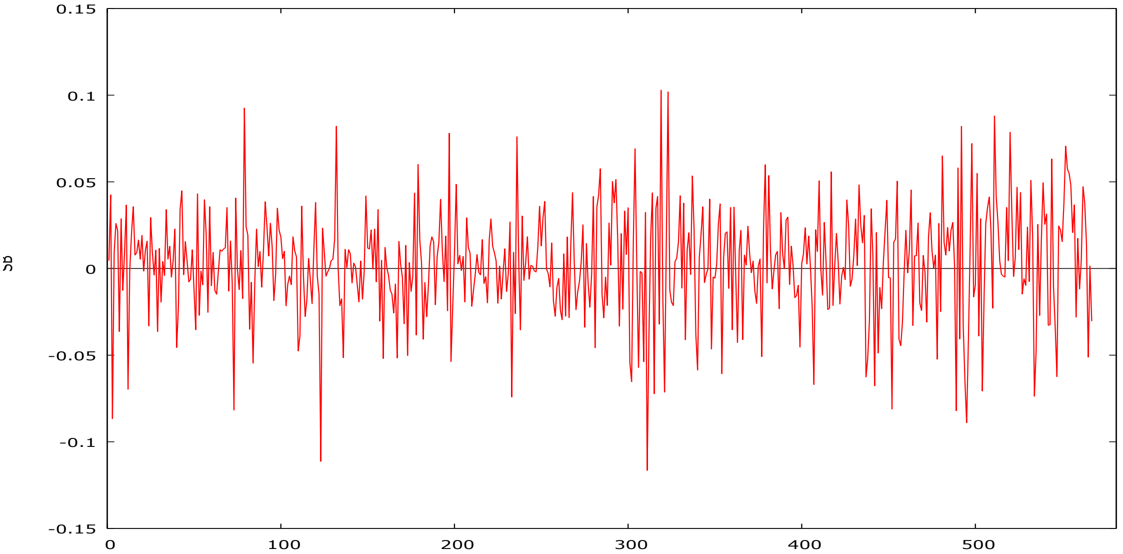


Figure A 4.3 Weekly value of the value factor (HML)

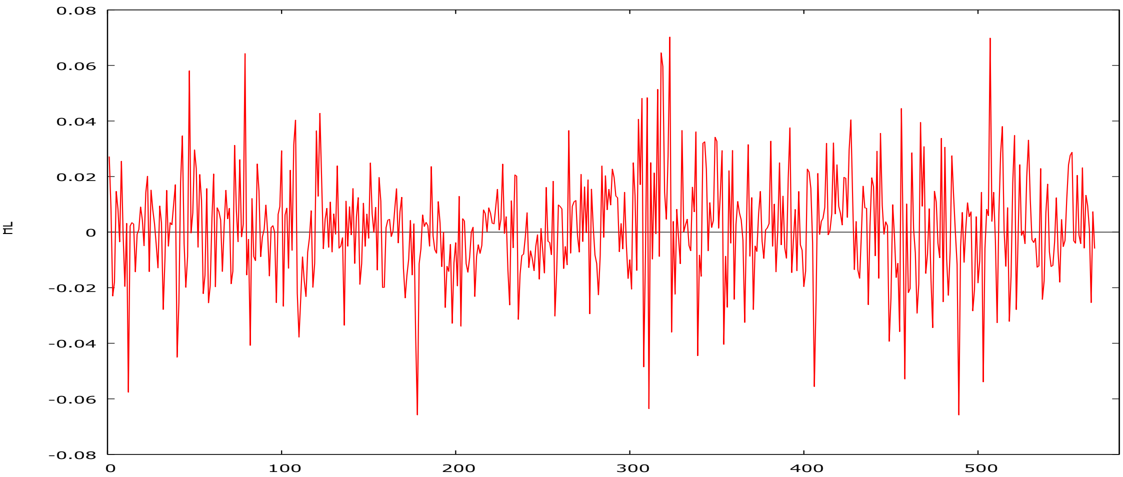


Figure A 4.4 Weekly value of the momentum factor (UMD)

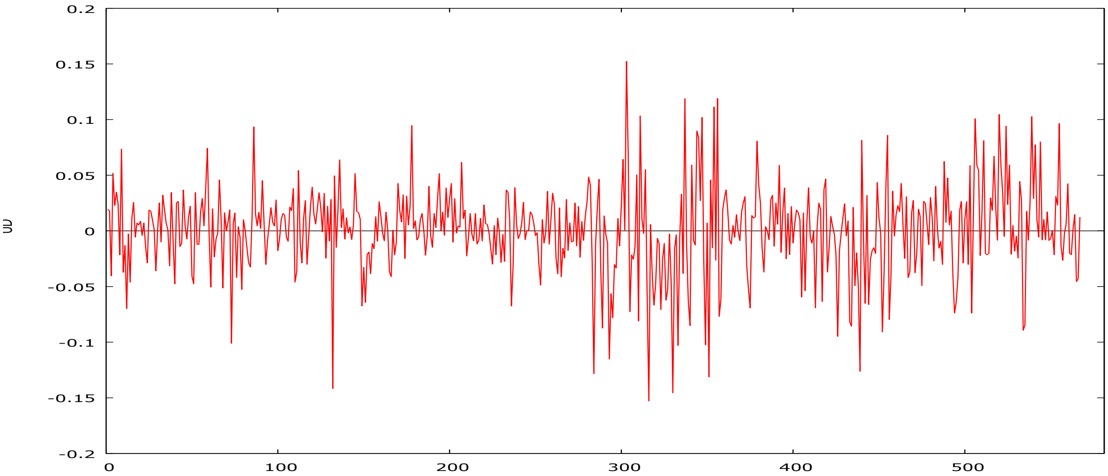
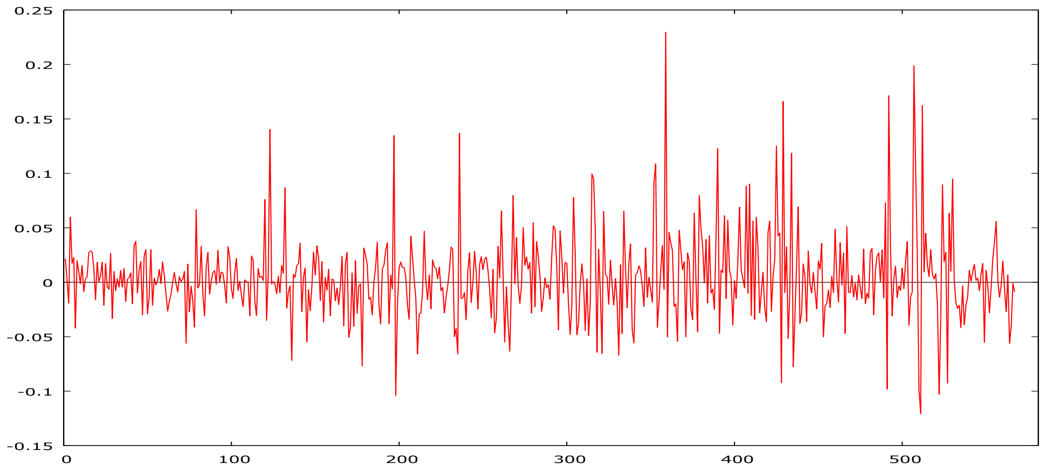


Figure A 4.5 Weekly value of the liquidity factor (IMV)



Appendix 4.2: Descriptive statistics of the emerging African market data sorted for survivorship bias and time-series plot of the factors

The summary statistics for the excess market returns, size, value, momentum, liquidity, skewness and kurtosis portfolios respectively are shown in Table A4.3 below.

Table A 4.3 Summary statistics of the emerging African market data, adjusted for survivorship bias

Summary statistics								
Variables	Mean	Median	Minimum	Maximum	Std dev.	CV	Skewness	Ex. Kurtosis
MKT	0.0028	0.0041	−0.1140	0.0726	0.0200	7.2291	−0.9894	3.9894
SMB	0.0015	0.0033	−0.0782	0.0781	0.0252	17.2380	−0.0503	0.4527
HML	0.0013	0.0016	−0.0643	0.0804	0.0180	14.1530	0.1187	1.5691
UMD	−0.0004	0.0016	−0.1373	0.1574	0.0333	89.3410	−0.2119	2.7261
IMV	0.0004	0.0017	−0.0913	0.0849	0.0262	65.2760	−0.1873	0.7619

Table A 4.4 Correlation matrix of the emerging African market data, adjusted for survivorship bias

Correlation matrix					
MKT	SMB	HML	UMD	IMV	
1	−0.1853	−0.0343	0.0698	−0.2512	MKT
	1	0.1742	−0.0470	0.6364	SMB
		1	−0.3509	0.0090	HML
			1	−0.0959	UMD
				1	IMV

The correlation matrix does not detect any overly high values of the correlation coefficient that may give rise to concerns of multicollinearity problem, except for the correlation between IMV and SMB. HAC standard errors will be used for the OLS to mitigate any potential effect on the results.

Figure A 4.6 Time-series plot of the weekly values of the market factor (MKT) for the unbiased dataset

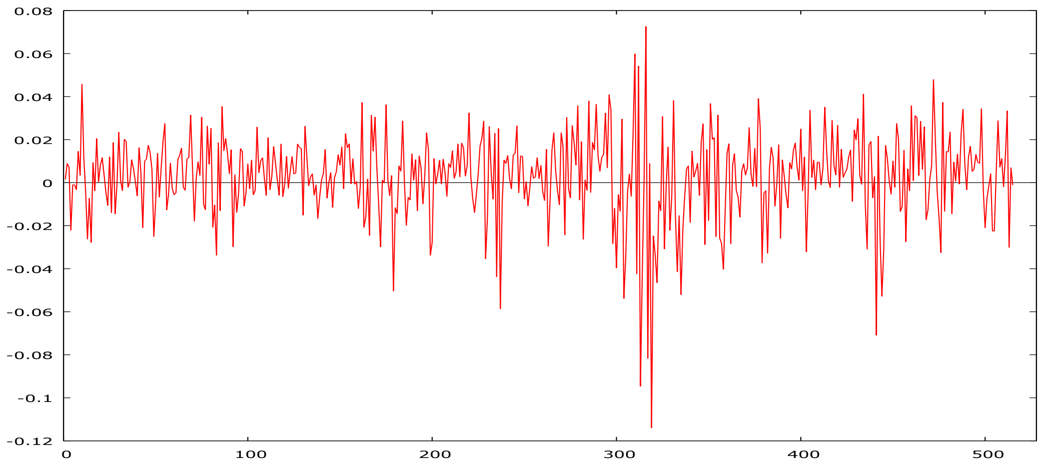


Figure A 4.7 Time-series plot of the weekly values of the size factor (SMB) for the unbiased dataset

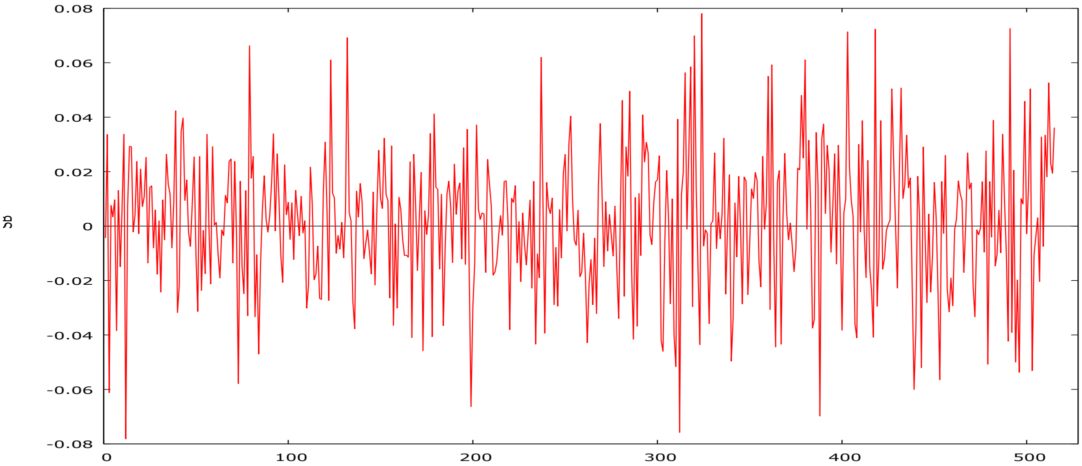


Figure A 4.8 Time-series plot of the weekly values of the value factor (HML) for the unbiased dataset

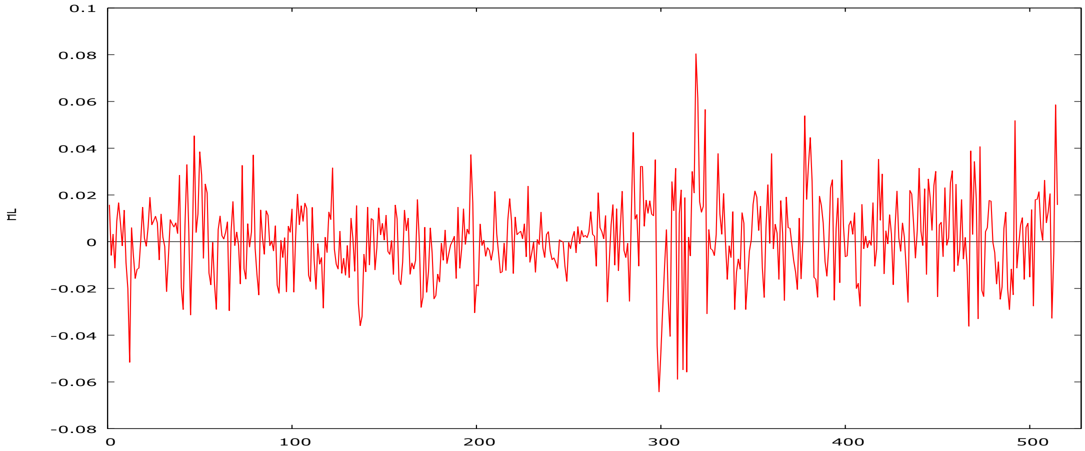


Figure A 4.9 Time-series plot of the weekly values of the momentum factor (UMD) for the unbiased dataset

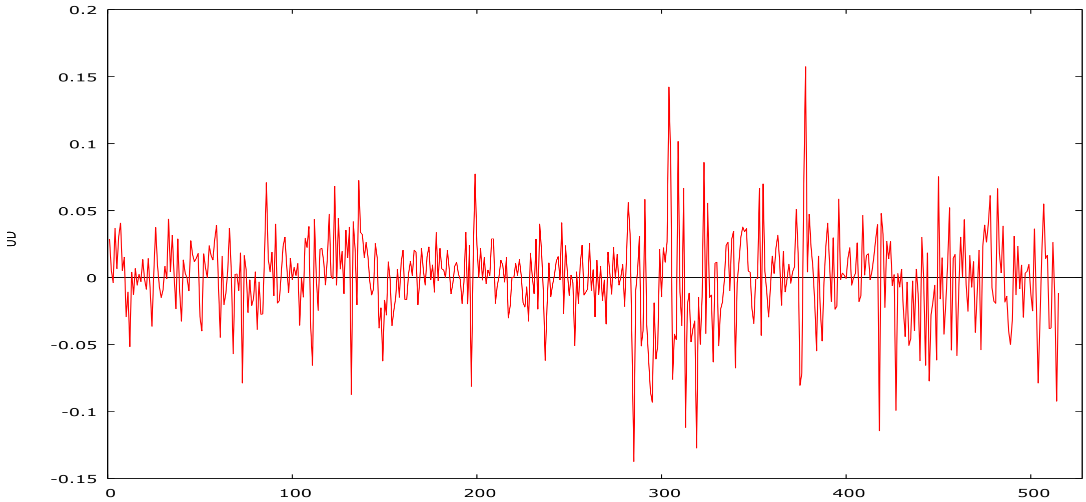
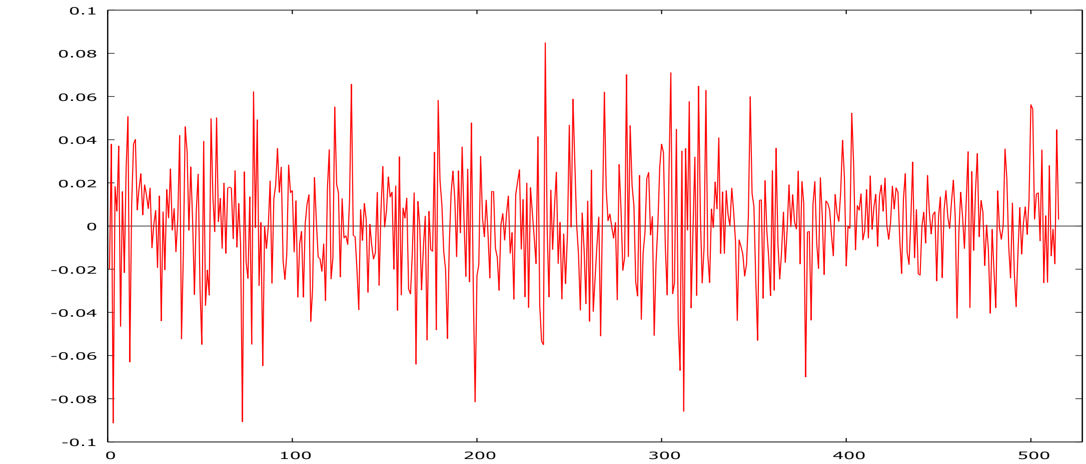


Figure A 4.10 Time-series plot of the weekly values of the liquidity factor (IMV) for the unbiased dataset



Appendix 4.3: Descriptive statistics of the basic material South African index not sorted for survivorship bias and time-series plot of the factors

Table A 4.5 Descriptive statistics of returns on the basic materials South Africa index not sorted for survivorship bias

	Minimum	Maximum	Mean	Std deviation	Skewness	Kurtosis
	statistic	statistic	statistic	statistic	statistic	statistic
MKT	−0.0891	0.1275	0.0009	0.0259	−0.162	2.263
SMB	−0.1283	0.0898	−0.0004	0.0262	−0.462	2.184
HML	−0.0975	0.0608	−0.0020	0.0229	−0.566	1.760
UMD	−0.1765	0.1927	0.0004	0.0364	0.089	6.018
IMV	−0.1571	0.0907	0.0027	0.0285	−0.563	3.770

Table A 4.6 Correlation coefficients of the portfolios in the South African market not sorted for survivorship bias

MKT	SMB	HML	UMD	IMV	
1	−0.2489	−0.1029	0.1976	−0.1772	MKT
	1	0.3740	−0.2724	0.5627	SMB
		1	−0.1575	0.3806	HML
			1	0.0102	UMD
				1	IMV

Correlation coefficients, 5% critical value (two-tailed) = 0.1114

The correlation matrix does not detect any overly high values of the correlation coefficient that may give rise to concerns of multicollinearity problem, except for the correlation between IMV and SMB. HAC standard errors will be used for the OLS to mitigate any potential effect on the results.

Tables 4.16 and 4.17 report descriptive statistics and correlation for the market, size, book-to-market, momentum and liquidity factors, indicated by MKT, SML, HML, UMD and IMV.

Plots of the weekly value of the market factor (MKT), the size factor (SMB), the value factor (HML), the momentum factor (UMD) and the liquidity factor (IMV), respectively, are shown below.

Figure A 4.11 Time-series plot of the weekly values of the market factor (MKT) for the biased dataset

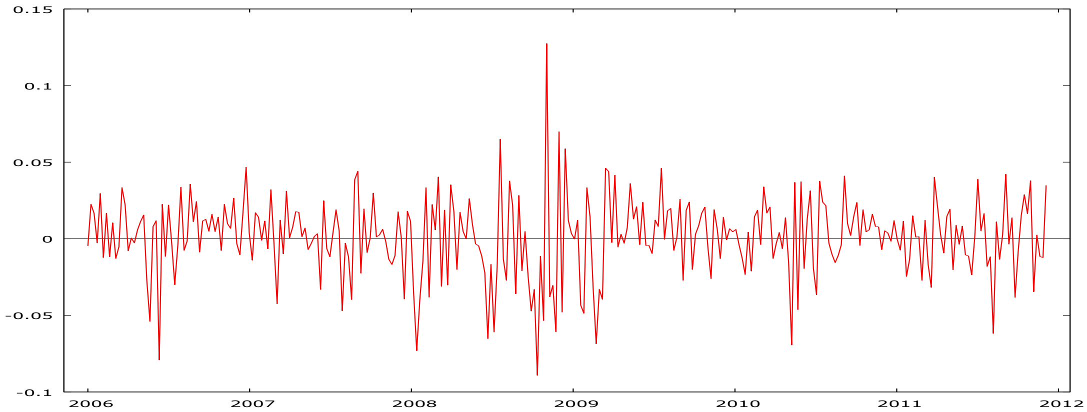


Figure A 4.12 Time-series plot of the weekly values of the size factor (SMB) for the biased dataset

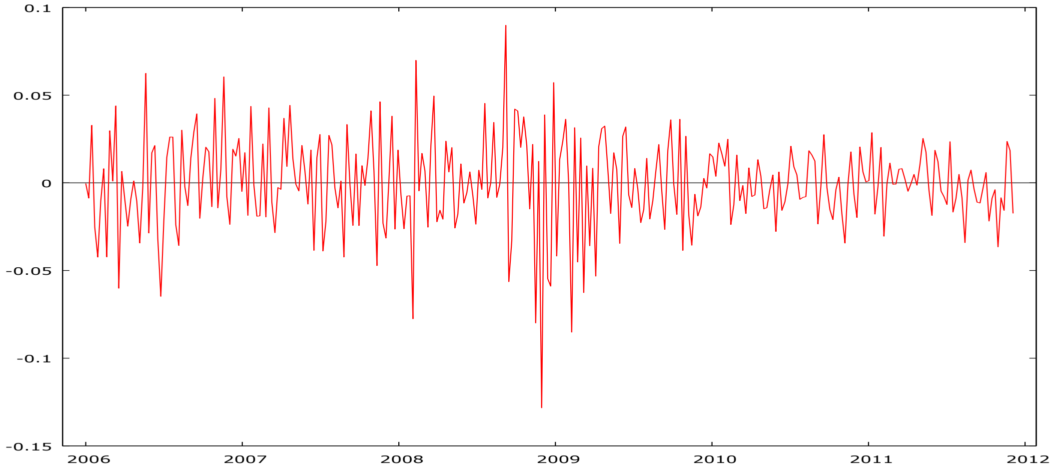


Figure A 4.13 Time-series plot of the weekly values of the value factor (HML) for the biased dataset

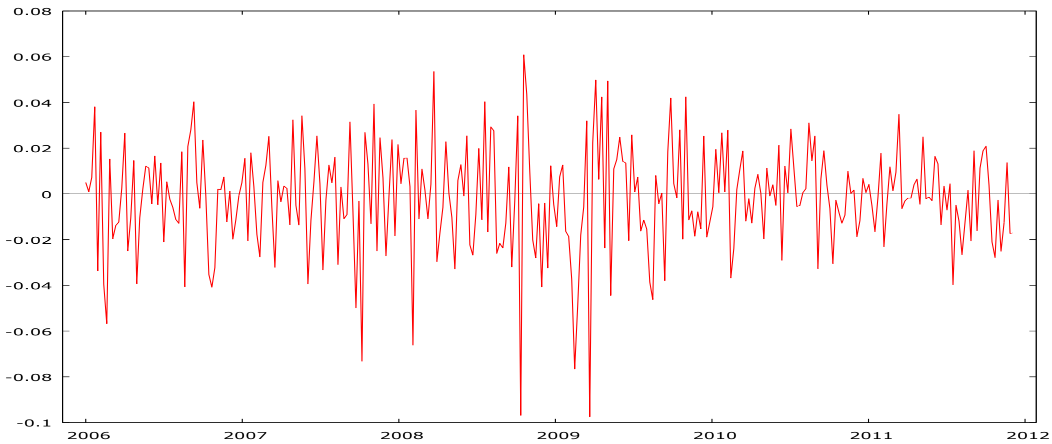


Figure A 4.14 Time-series plot of the weekly values of the momentum factor (UMD) for the biased dataset

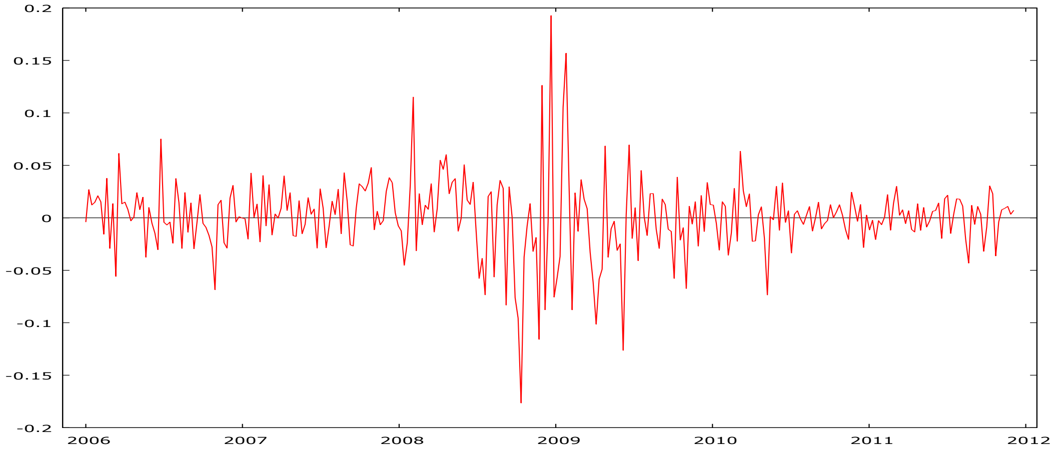
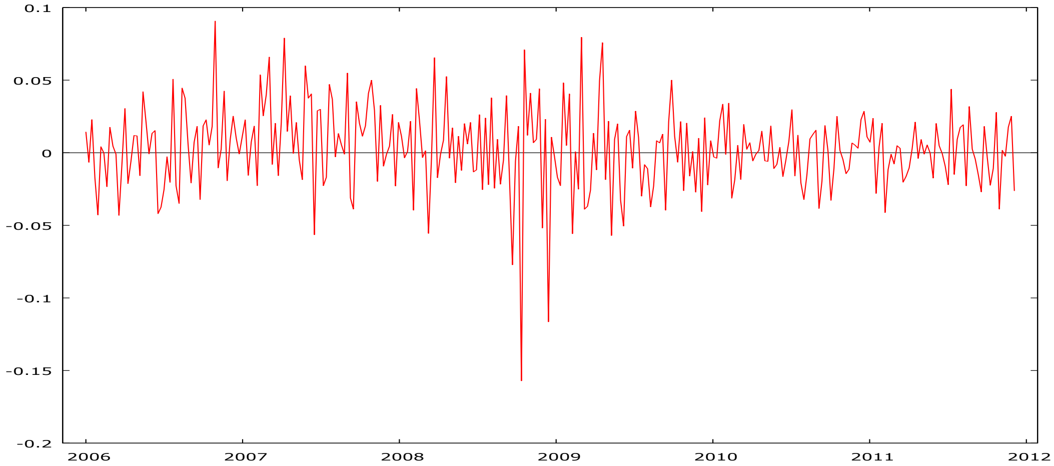


Figure A 4.15 Time-series plot of the weekly values of the liquidity factor (IMV) for the biased dataset



Appendix 4.4: Descriptive statistics of the basic materials South African index sorted for survivorship bias and time-series plot of the factors

Table A 4.7 Summary statistics for the basic materials South African index sorted for survivorship bias

Variable	Mean	Median	Minimum	Maximum	Std dev.	Skewness	Ex. kurtosis
RmMRf	0.0031	0.0044	−0.0867	0.1298	0.0225	−0.1877	2.8244
SMB	0.0002	−0.0004	−0.1628	0.1045	0.0282	−0.1977	2.9217
HML	−0.0002	−0.0003	−0.1373	0.0982	0.0221	−0.3739	4.3700
UMD	0.0009	0.0037	−0.1400	0.1655	0.0379	−0.1800	2.2074
IMV	0.0010	0.0016	−0.1576	0.0937	0.0257	−0.4918	3.6090
Skewness	0.9003	0.8120	−8.7240	8.4541	1.4329	−0.6081	17.3867
Kurtosis	0.9927	0.9879	0.9704	1.0379	0.0132	0.9132	−0.0313

Table A4.7:[124] Summary statistics for the South Africa basic materials index from 2005-01-07 to 2015-01-02

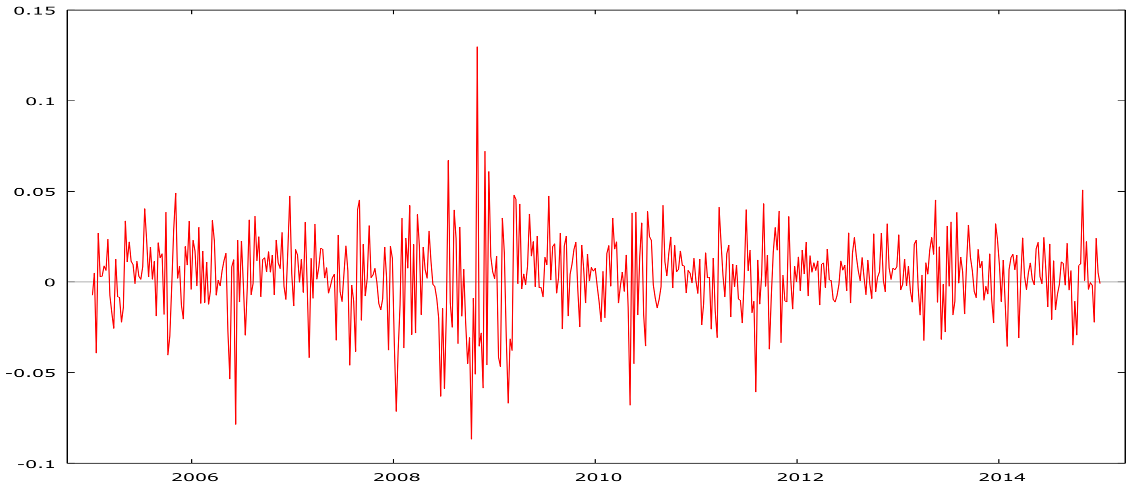
Table A 4.8 Correlation coefficients for the basic materials South African index sorted for survivorship bias

RmMRf	SMB	HML	UMD	IMV	
1	−0.309	0.1336	0.1091	−0.2988	RmMRf
	1	−0.2861	−0.2195	0.7617	SMB
		1	0.3995	−0.1744	HML
			1	−0.1576	UMD
				1	IMV

5% critical value (two-tailed) = 0.0858

The correlation matrix does not detect any overly high values of the correlation coefficient that may give rise to concerns of multicollinearity problem, except for the correlation between IMV and SMB. HAC standard errors will be used for the OLS to mitigate any potential effect on the results.

Figure A 4.16 Time-series plot of the weekly values of the market factor (MKT) for the unbiased dataset – South Africa



[124] Data is survivorship-bias-free.

Figure A 4.17 Time-series plot of the weekly values of the size factor (SMB) for the unbiased dataset – South Africa

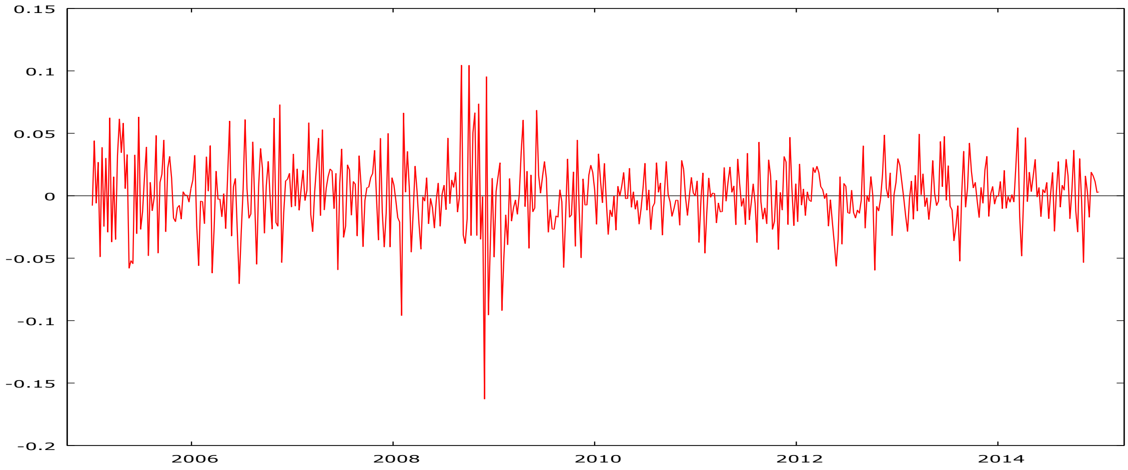


Figure A 4.18 Time-series plot of the weekly values of the value factor (HML) for the unbiased dataset – South Africa

Figure A 4.19 Time-series plot of the weekly values of the momentum factor (UMD) for the unbiased dataset – South Africa

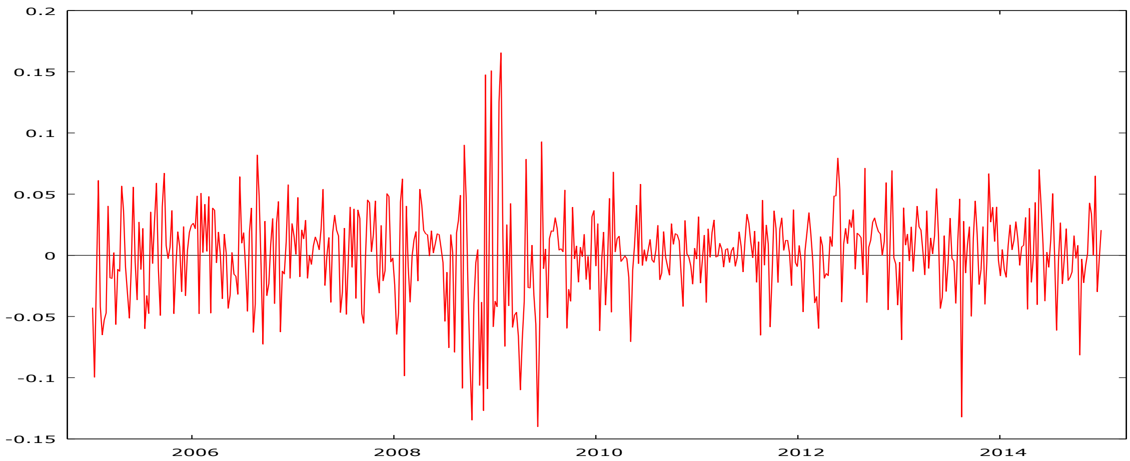


Figure A 4.20 Time-series plot of the weekly values of the liquidity factor (IMV) for the unbiased dataset – South Africa

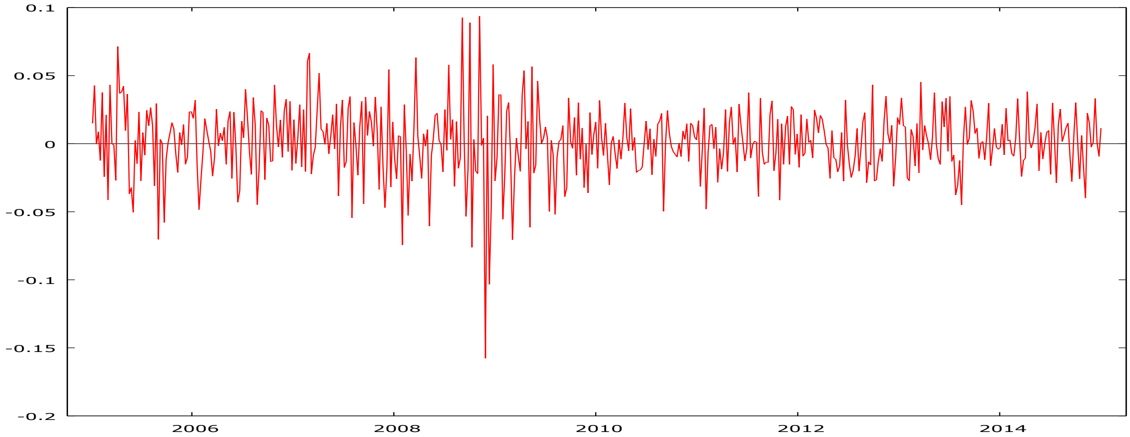


Table A 4.9 South Africa's basic materials index attrition rate

A: South Africa's basic materials index attrition rate					
Year	Year start	Entry	Exit	Year end	Attrition rate
2004	24	3	1	26	4%
2005	26	0	1	25	4%
2006	25	25	11	39	44%
2007	39	4	4	39	10%
2008	39	3	2	40	5%
2009	40	1	2	39	5%
2010	39	2	1	40	3%
2011	40	3	4	39	10%
2012	39	1	7	33	18%
2013	33	2	5	30	15%
2014	30	4	3	31	10%
Average attrition rate					12%

Table A 4.10 Egypt's basic materials index attrition rate

B: Egypt's Basic Materials index attrition rate					
Year	Year start	Entry	Exit	Year end	Attrition rate
2004	6	0	0	6	0%
2005	6	0	0	6	0%
2006	6	0	0	6	0%
2007	6	0	0	6	0%
2008	6	0	0	6	0%
2009	6	14	0	20	0%
2010	20	2	6	16	30%
2011	16	1	5	12	31%
2012	18	0	3	15	17%
2013	15	1	1	15	7%
2014	15	2	5	12	33%
Average attrition rate					12%

Table A 4.11 Morocco's basic materials index attrition rate

C: Morocco's basic materials index attrition rate					
Year	Year start	Entry	Exit	Year end	Attrition rate
2004	3	0	0	3	0%
2005	3	0	0	3	0%
2006	3	0	0	3	0%
2007	3	0	0	3	0%
2008	3	0	0	3	0%
2009	3	3	0	6	0%
2010	6	3	2	7	33%
2011	7	0	0	7	0%
2012	7	0	1	6	14%
2013	6	1	1	6	17%
2014	6	1	3	4	50%
Average attrition rate					11%

Figure A 4.21 Time-series plot of the weekly returns on the biased basic materials emerging African index

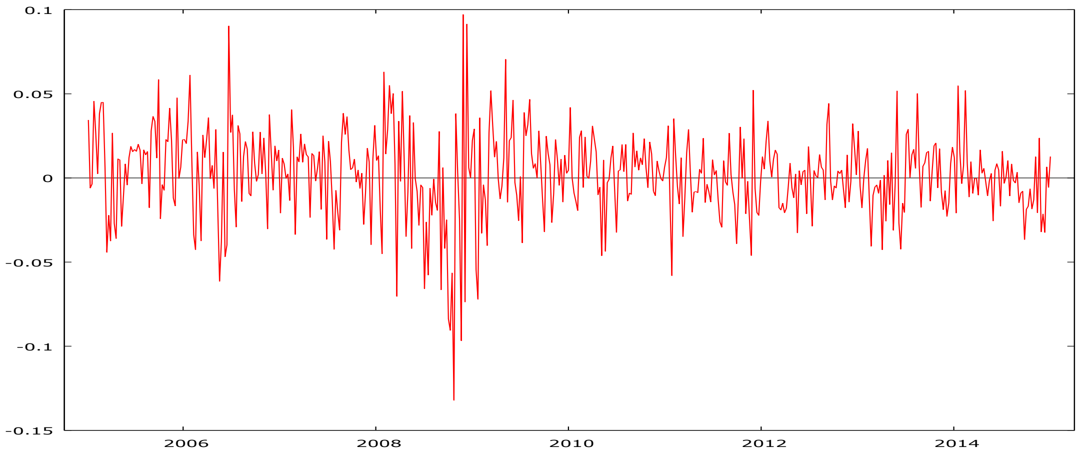


Figure A 4.22 Time-series plot of the weekly returns on the unbiased basic materials emerging African index

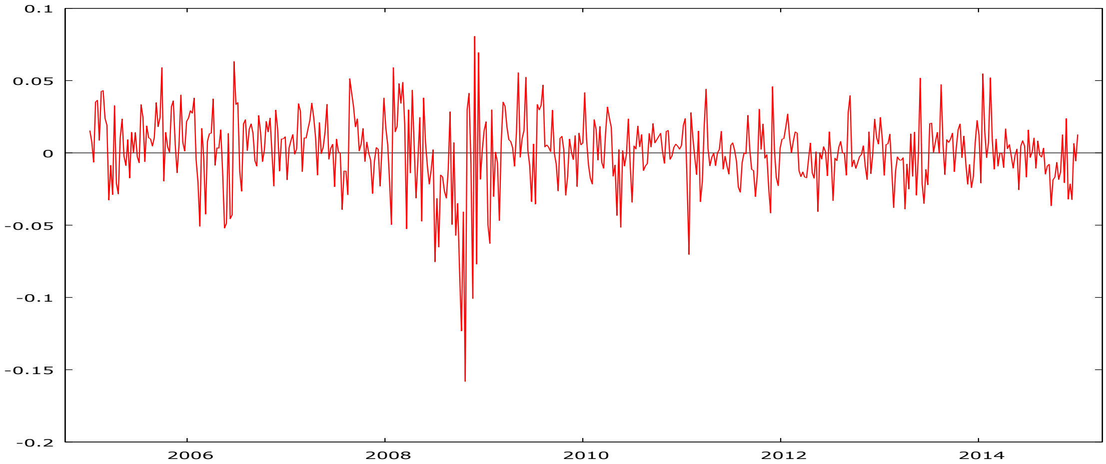


Figure A 4.23 Time-series plot of the weekly returns on the biased basic materials South Africa index

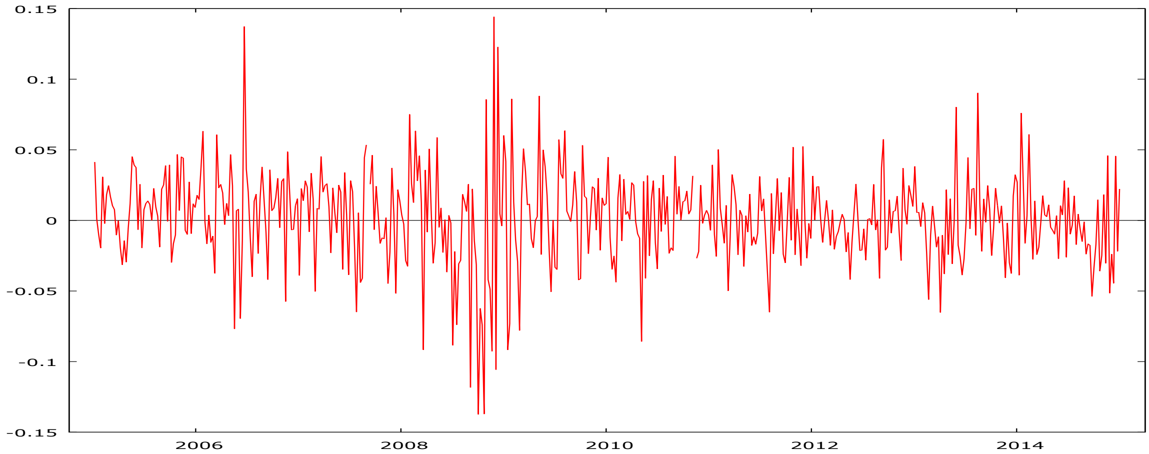
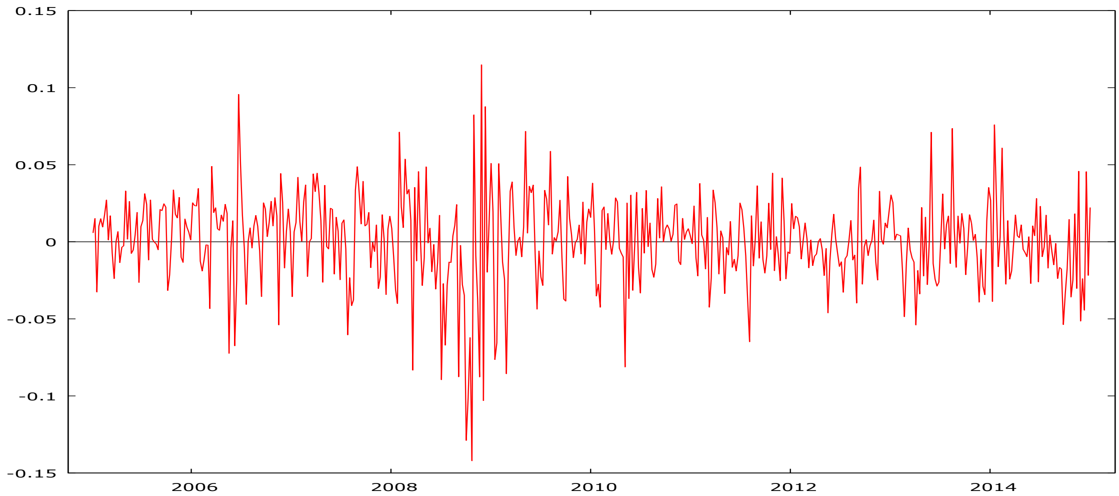


Figure A 4.24 Time-series plot of the weekly returns on the unbiased basic materials South Africa index



5 ASSET-PRICING MODELS IN THE SOUTH AFRICAN BASIC MATERIALS INDEX.

5.1 Introduction and structure of chapter

With increasing scepticism about the performance of the one-factor CAPM, especially in emerging markets as established in Section 2.2 of Chapter 2, Hearn and Piesse (2009) insist that this diverging definition of risk needs to be accounted for in modelling the returns relationship. This is supported by Dey (2005) and Lischewski and Voronkova (2012), who indicate that the diverging definition of risk around world markets needs to be recognised within models that seek to explain the behaviour of returns. This divergence from the one-factor CAPM is more pronounced in the African markets due to severe illiquidity and thin trading, as identified in Levine and Zervos (1998), and financial segmentation/integration as seen in Stulz (1999). However, this divergence also varies across African countries due to the varying degree of integration with developed markets. This chapter will also investigate the liquidity premium.

A huge part of this risk results from the severe illiquidity and thin trading problems in the African market, as stated in Allen, Otchere and Senbet (2011). According to Pagano (1989), when markets are thin, volatility increases along with the tendency for asset prices to react adversely to the orders of traders. This can often lead to instability in beta, which is contrary to the assumption of the static CAPM. With the rationale for the importance of liquidity and higher moments within asset-pricing models identified within African equity markets (Sections 2.4 and 2.9 of the literature review in Chapter 2), this chapter will assess the importance of these factors in the South African market, the emerging African market and the frontier African market.

Given the size of the South African market and its level of development/integration with world markets, this chapter will also analyse the emerging African market excluding South Africa. This is because I expect different characteristics within the index that excludes the South African market, given the size and classification of South Africa as an advanced emerging African market, as highlighted in Section 3.2 of Chapter 3. Also, I expect different factors to explain returns in the South African market, the emerging African market and the frontier African market.

This chapter will thus investigate the performance of the static Sharpe-Lintner CAPM, the three-factor Fama-French (1993) model, the four-factor Carhart (1997) model and the importance of liquidity in explaining the cross-section of asset returns in the African stock market. It will also investigate the question of whether higher moments have any explanatory power within a four-moment asset-pricing model in this market. Given the implication of contagion, as discussed in the literature review (Section 2.6), the impact of exogenous shock (contagion as identified in Section 3.6) on the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market, will also be examined.

Section 5.2 highlights the descriptive statistics of the emerging African market, while Sections 5.3, 5.4, 5.5 and 5.6 highlight the results within the South African market, the emerging African market index, the emerging African market index excluding South Africa and the frontier African market, respectively. These empirical findings are analysed, with the chapter conclusion and chapter appendices provided in Sections 5.7 and 5.8, respectively.

5.2 Descriptive statistics for the Indices formed[125]

The descriptive statistics for the excess market returns portfolio, size portfolio, value portfolio, momentum portfolio, liquidity portfolio, skewness and kurtosis respectively are shown in the tables below.

Table 5.1 Descriptive statistics for the South African basic materials index (full sample, 2004-2014)

Variable	Mean	Median	Minimum	Maximum	Std dev.	CV	Skewness	Ex. kurtosis
MKT[126]	0.0035	0.0049	−0.0867	0.1298	0.0220	6.3673	−0.2372	2.9051
SMB	0.0005	−0.0004	−0.1628	0.1045	0.0285	57.463	−0.1554	2.4852
HML	−0.0001	−0.0003	−0.0743	0.0982	0.0210	267.95	0.0686	2.2372
UMD	0.0016	0.0041	−0.1400	0.1654	0.0374	23.387	−0.1799	2.0894
IMV	0.0017	0.0021	−0.1576	0.0937	0.0256	15.126	−0.4557	3.3578
S_i	0.9145	0.8174	−8.7239	8.4541	1.3748	1.5033	−0.6355	18.898
K_i	0.9942	0.9876	0.9627	1.1648	0.0214	0.0215	3.5303	19.798

[125] The descriptive statistics and correlation matrix within this section are different from those in Chapter 4 as they are not the same sample period.

[126] MKT stands for Rm-Rf, which is the return on the market less the risk-free rate and defined in Fama and French (1993).

Initial indications from the summary statistics in Table 5.1 show a positive weekly average return of 0.35% for the market portfolio, with a standard deviation of 2.2% and a positive weekly average return of 0.05% on the size portfolio, with a standard deviation of 2.85%. However, the portfolio formed on value had a negative weekly average return of −0.01% with a standard deviation of 2.1%. The momentum factor had a weekly average return of 0.16% and a standard deviation of 3.74%, while the factor formed on liquidity had a weekly average return of 0.17% and a standard deviation of 2.56%. The higher-order moments of skewness and kurtosis had an average value of 0.92 and 0.99 respectively, with a standard deviation of 137.48% and 2.14% respectively.

The average return on the portfolio formed on size is in line with the findings in Banz (1981) and Quiros and Timmermann (2000). The average returns on the value portfolio suggest a departure from the findings in Ang and Chen (2007) on the importance of the value factor to the findings of Loughran (1997), who suggests the increasing reversal and unimportance of the value factor. The momentum factor conforms to the expectations in Jegadeesh and Titman (1993), while the liquidity premium identified in Table 5.1 conforms with the findings in Lischewski and Voronkova (2012). However, as stated in Horowitz et al. (2000a), identifying whether the magnitude of these factors is significant remains the major issue.

Table 5.2 Correlation coefficients for the South African basic materials index portfolios

MKT	SMB	HML	UMD	IMV	S_i	K_i	
1	−0.3001	0.0802	0.0984	−0.2782	−0.0447	0.0789	MKT
	1	−0.2710	−0.1620	0.6962	0.0357	−0.0637	SMB
		1	0.3511	−0.2118	0.0111	−0.0205	HML
			1	−0.1207	0.0370	0.0253	UMD
				1	0.0317	0.0102	IMV
					1	0.1472	S_i
						1	K_i

Table 5.2 shows the correlation coefficients between the risk factors. There are no concerns about a multicollinearity problem.

Figures 5.1, 5.2, 5.3, 5.4, 5.5, 5.6, 5.7 plot the weekly values of the market factor (MKT), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the liquidity factor (IMV), skewness and kurtosis, respectively.[127]

Figure 5.1 Weekly values of returns on the market index (MKT) for the South African basic materials index

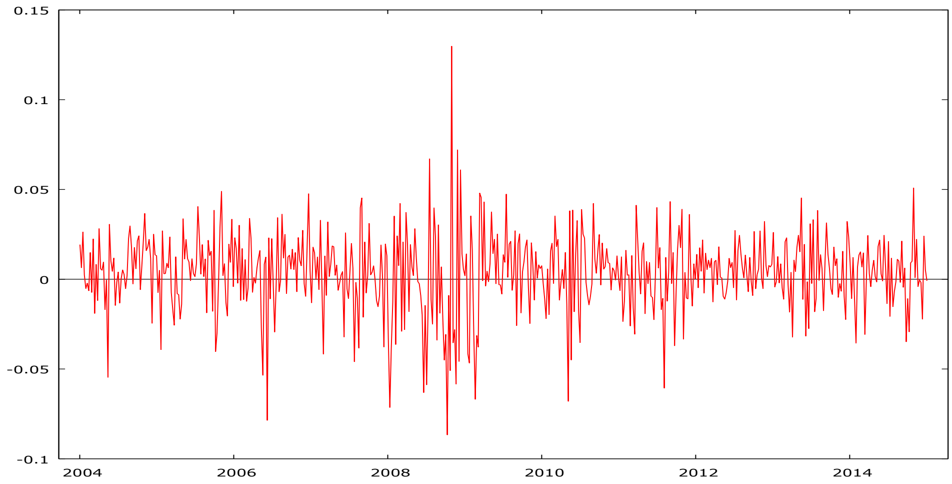
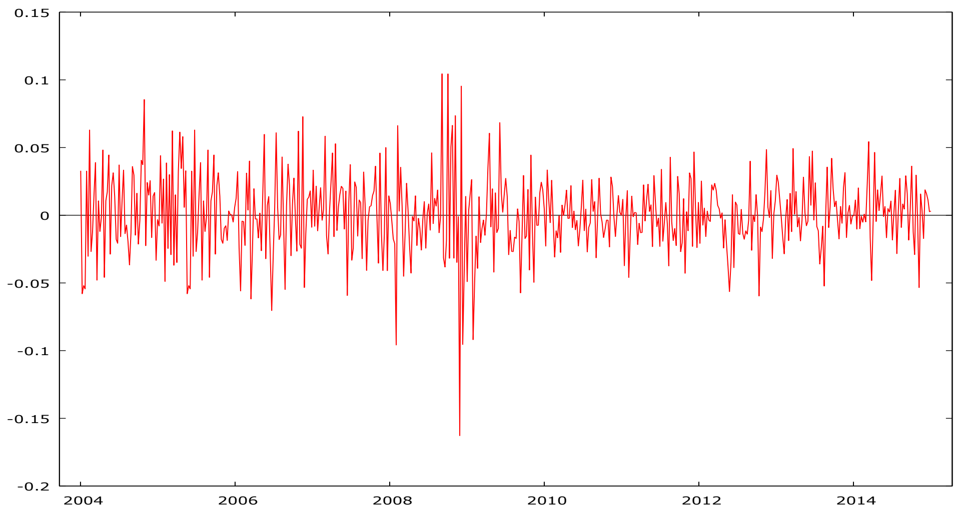


Figure 5.2 Weekly values of the returns on the portfolio formed on size (SMB) for the South African basic materials index



[127] The frequency distribution with the Doornik-Hansen test for normality for each variables and their correlograms are shown in the chapter appendix. The correlograms show the autocorrelation function using a maximum of 27 lags. The Ljung–Box Q-statistic is not shown but is available on request from the author.

Figure 5.3 Weekly values of the returns on the portfolio formed on value (HML) for the South African basic materials index

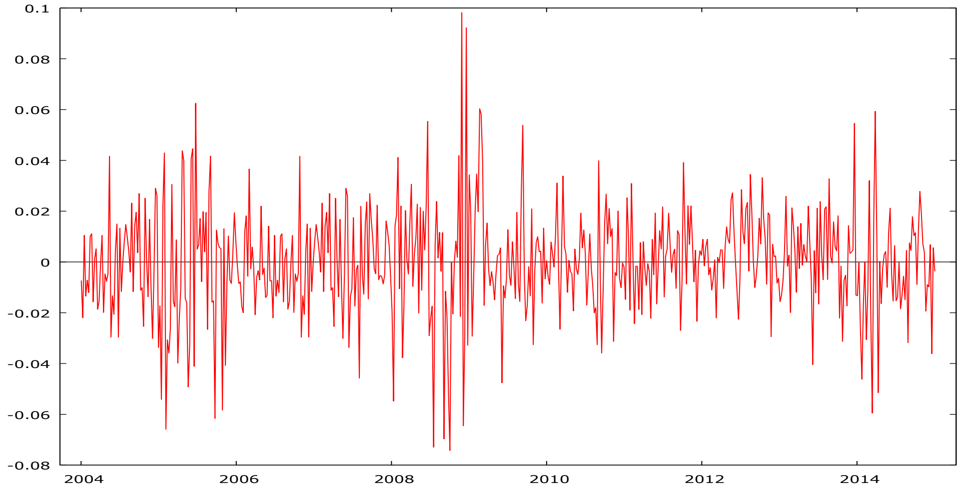


Figure 5.4 Weekly values of the returns on the portfolio formed on the momentum factor (UMD) for the South African basic materials index

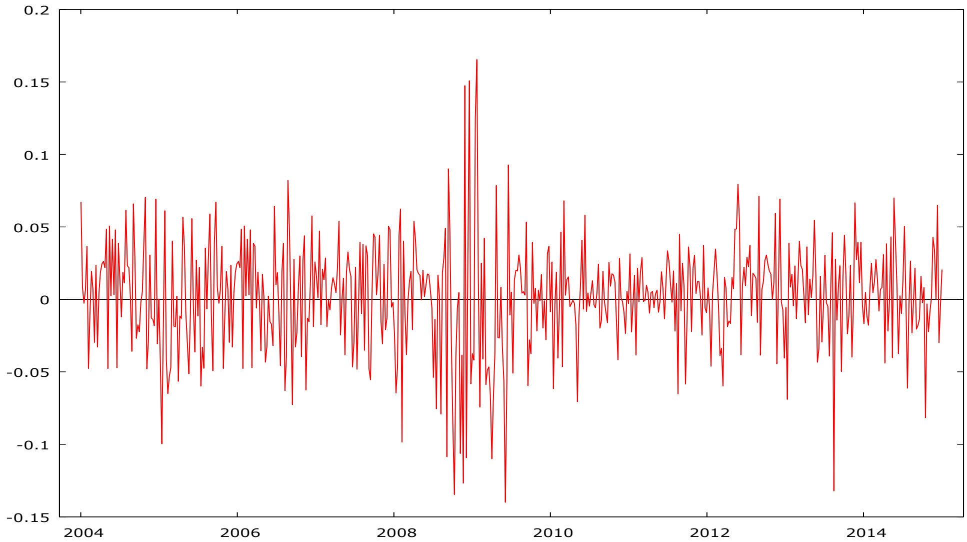


Figure 5.5 Weekly values of the returns on the portfolio formed on the liquidity (IMV) for the South African basic materials index

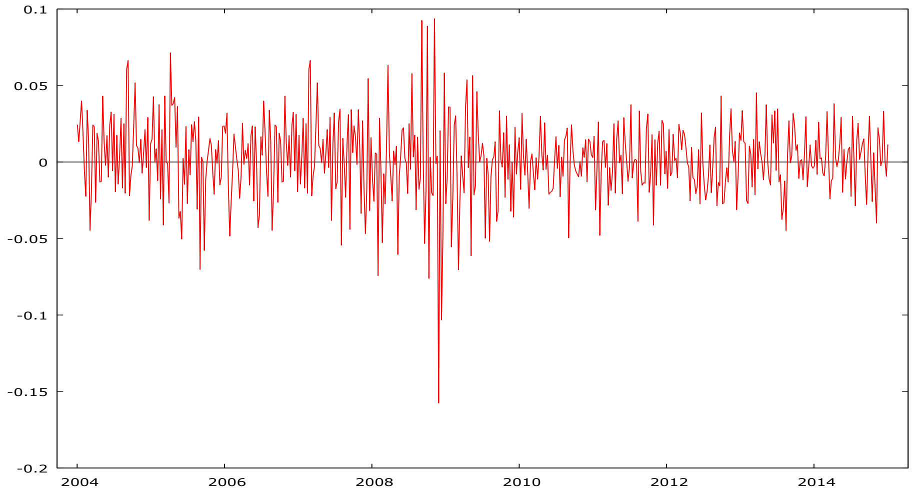


Figure 5.6 Time-series weekly skewness (S_i) values for the South African basic materials index

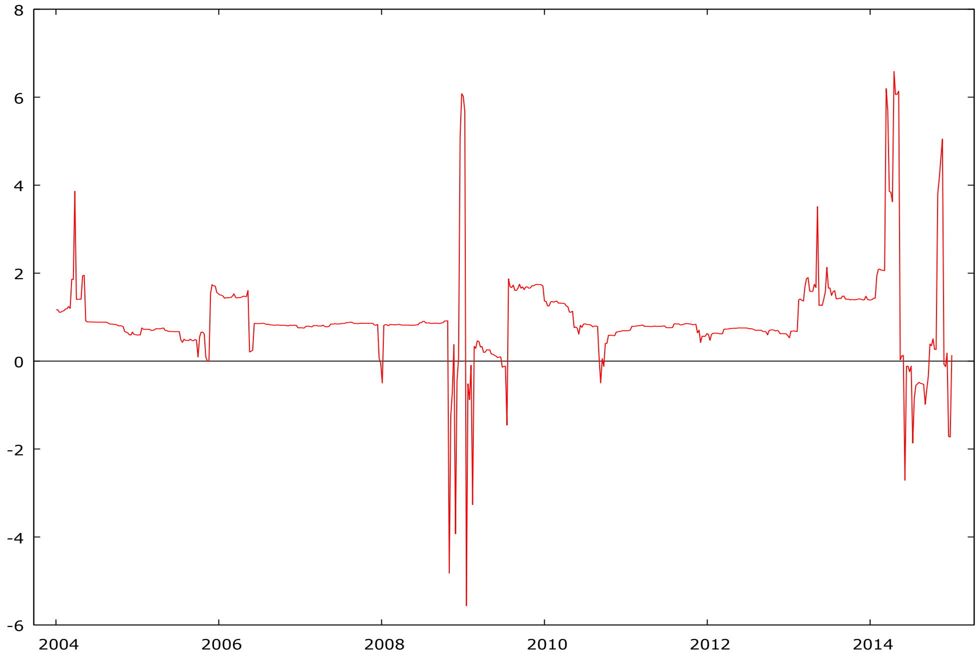


Figure 5.7 Time-series weekly kurtosis (K_i) values for the South African basic materials index

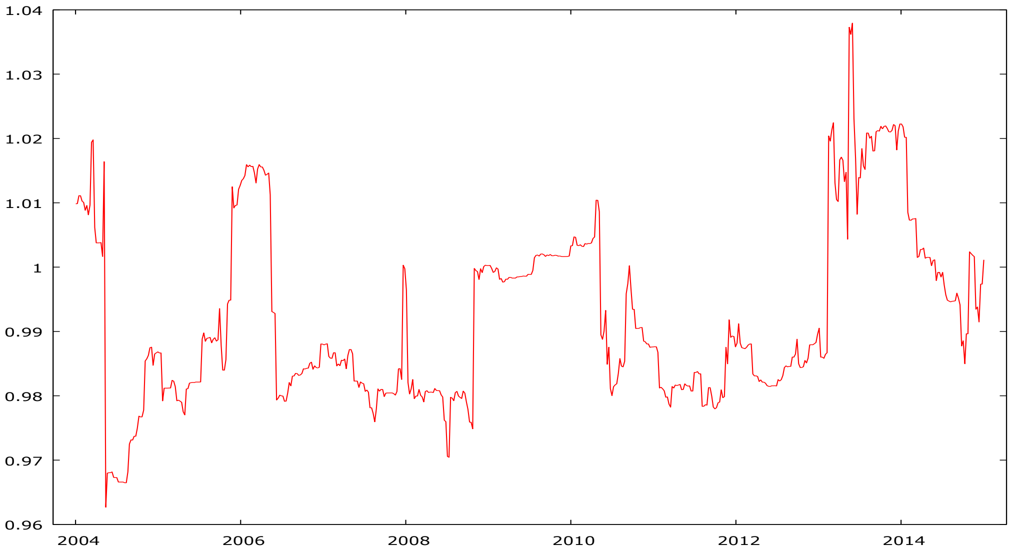


Table 5.3 Descriptive statistics for the emerging African market index portfolios. (full sample, 2004-2014)

Variable	Mean	Median	Minimum	Maximum
MKT[128]	0.0033	0.0042	−0.1140	0.0726
SMB	0.0025	0.0040	−0.0758	0.0786
HML	0.0014	0.0013	−0.0643	0.0804
UMD	0.0009	0.0018	−0.1373	0.1422
IMV	0.0002	0.0017	−0.1029	0.0948
S_i	0.7724	0.8350	−6.5429	6.2220
K_i	0.9907	0.9893	0.9692	1.0328
Variable	Std dev.	CV	Skewness	Ex. kurtosis
MKT	0.0188	5.6838	−0.9601	4.4530
SMB	0.0259	10.4505	0.0370	0.2781
HML	0.0177	13.0213	0.1654	1.4352
UMD	0.0332	38.0135	−0.2014	2.0362
IMV	0.0271	172.1930	−0.1762	1.2305
S_i	1.1425	1.4791	−0.5855	10.0921
K_i	0.0126	0.0128	1.0183	1.6059

Initial indications from the summary statistics in Table 5.3 show a positive weekly average return of 0.33% for the market portfolio, with a standard deviation of 2.4%, and a positive weekly average return of 0.25% on the size portfolio, with a standard deviation of 2.59%. The portfolio formed on value had a weekly average return of 0.14%, with a standard deviation of 1.77%, while the portfolio formed on the momentum factor had a weekly average return of 0.09% and a standard deviation of 3.32%. The factor formed on liquidity had a weekly average return of 0.02% and a standard deviation of 2.71%. The higher-order moments of skewness and kurtosis had an average value of 0.77 and 0.99, respectively, with a standard deviation of 114.25% and 1.26%, respectively.

The positive market returns are consistent with the findings in Sharpe, Alexander and Bailey (1999). The size premium highlighted in the summary statistics is in line with the expectation of Banz (1981), while the value factor mirrors the expectations in Stattman (1980). The positive mean of the momentum factor is consistent with the findings in Chui et al. (2003), while the liquidity premium is highlighted in Correia and Uliana (2004). However, as stated in Horowitz

[128] MKT stands for Rm-Rf, which is the return on the market less the risk-free rate and defined in Fama and French (1993).

et al. (2000a), identifying whether the magnitude of these factors is significant remains the major issue.

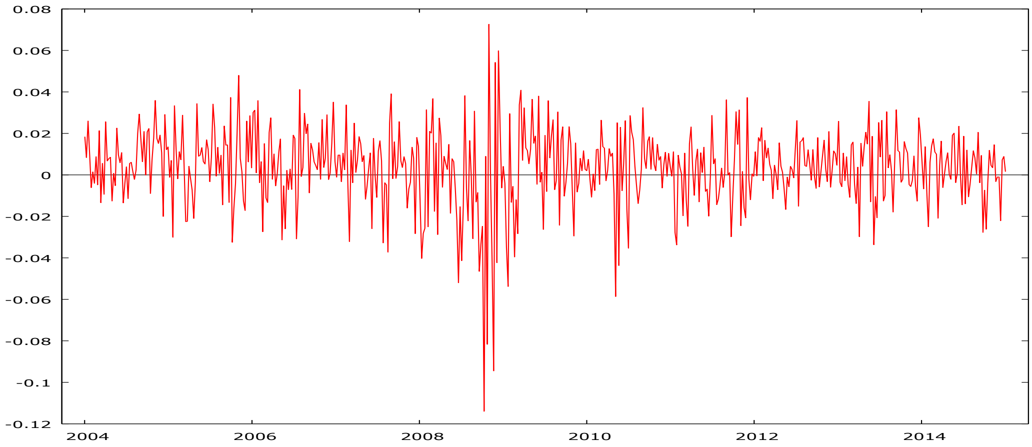
Table 5.4 Correlation coefficients for the emerging African market index portfolios

MKT	SMB	HML	UMD	IMV	S_i	K_i	
1	−0.1624	−0.0323	0.0812	−0.2342	0.0087	0.1285	MKT
	1	0.1954	0.0427	0.5594	−0.0169	−0.0176	SMB
		1	−0.3174	0.0383	0.0077	0.0826	HML
			1	-0.0209	0.0115	0.0269	UMD
				1	0.0928	0.0139	IMV
					1	0.0851	S_i
						1	K_i

Table 5.4 shows the correlation between the explanatory variables. It does not detect any overly high value of the correlation coefficients that may give rise to any concerns about a multicollinearity problem.

Figures 5.8, 5.9, 5.10, 5.11, 5.12, 5.13 and 5.14 plot the weekly values of the market factor (MKT), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the liquidity factor (IMV), skewness and kurtosis, respectively.[129]

Figure 5.8 Weekly values of returns on the market index (MKT) for the emerging African market index



[129] The frequency distribution with the Doornik-Hansen test for normality for each variables and their correlograms are shown in the chapter appendix. The correlograms show the autocorrelation function using a maximum of 27 lags. The Ljung–Box Q-statistic is not shown but is available on request from the author.

Figure 5.9 Weekly values of the returns on the portfolio formed on size (SMB) for the emerging African market index

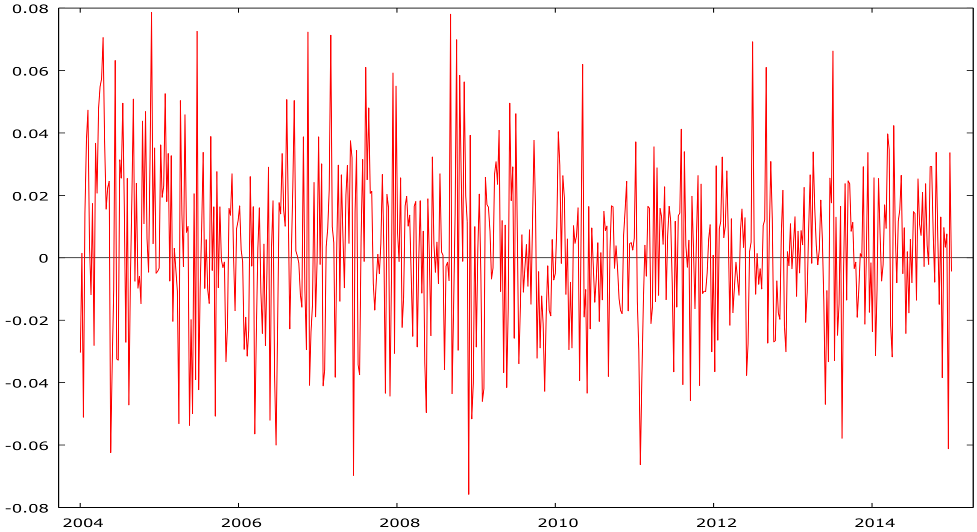


Figure 5.10 Weekly values of the returns on the portfolio formed on value (HML) for the emerging African market index

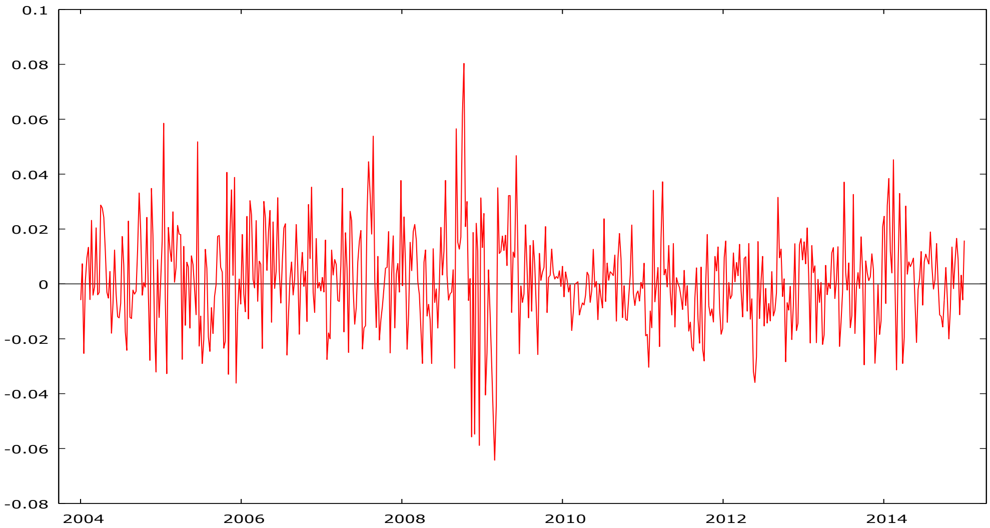


Figure 5.11 Weekly values of the returns on the portfolio formed on the momentum factor (UMD) for the emerging African market index

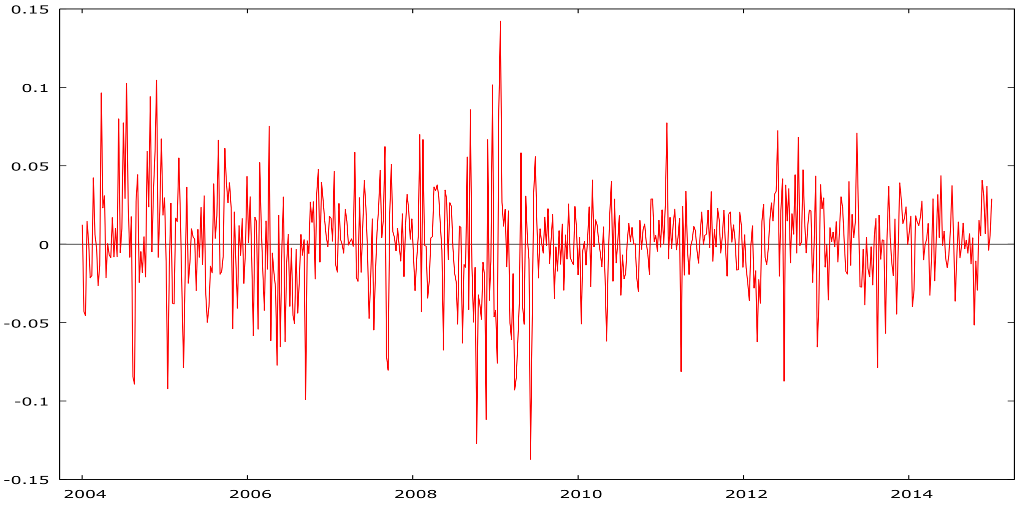


Figure 5.12 Weekly values of the returns on the portfolio formed on the liquidity (IMV) for the emerging African market index

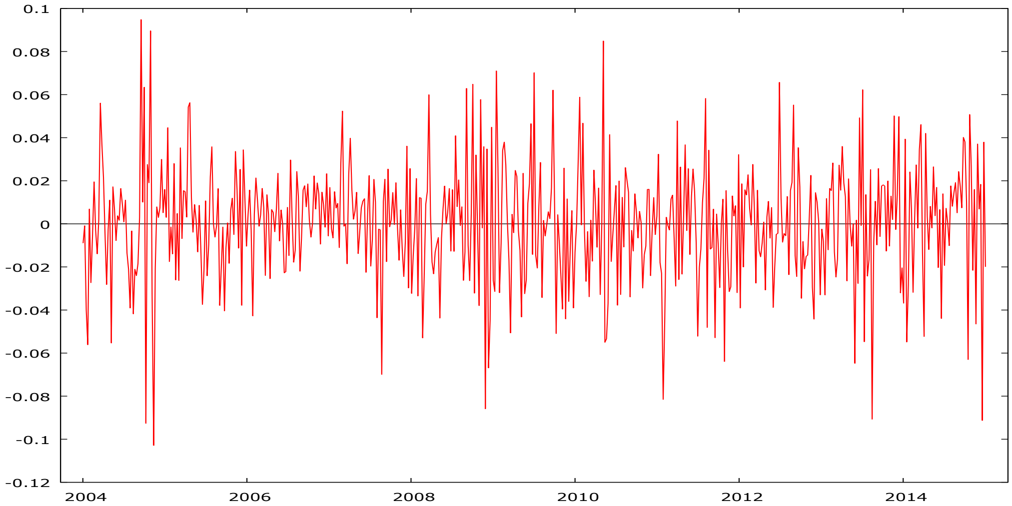


Figure 5.13 Time-series weekly skewness (S_i) values for the emerging African market index

Figure 5.14 Time-series weekly kurtosis (K_i) values for the emerging African market index

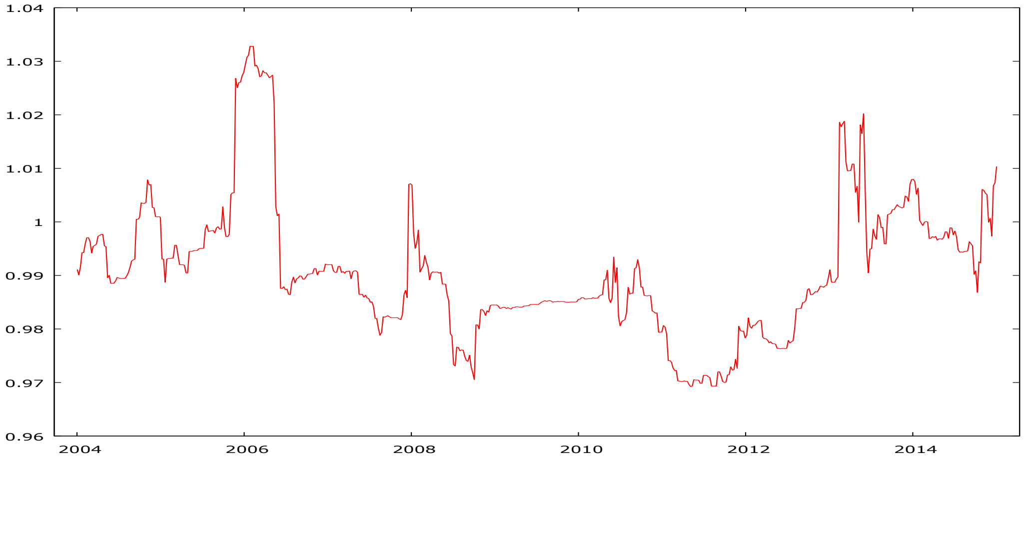


Table 5.5 Summary statistics for the emerging African market index ex. South Africa portfolios. (full sample, 2004-2014)

Variable	Mean	Median	Minimum	Maximum
MKT	0.0022488	0.0044849	−0.143901	0.0835953
SMB	0.0028003	0.0020887	−0.087066	0.132079
HML	0.0030757	0.0026746	−0.138809	0.151217
UMD	0.0031432	0.0038385	−0.212984	0.303716
IMV	0.0014879	0.0018897	−0.139173	0.102542
S_i	0.9564	0.980192	−0.091603	3.05011
K_i	0.99891	0.99752	0.9902	1.0115
Variable	Std dev.	CV	Skewness	Ex. kurtosis
MKT	0.027076	12.04	−1.08821	4.59447
SMB	0.024024	8.579	0.152052	2.18541
HML	0.0292616	9.51383	0.115868	2.19912
UMD	0.0452134	14.3846	−0.317102	6.93382
IllqLiq	0.0257778	17.3246	−0.098843	2.3005
S_i	0.216612	0.226487	1.40221	24.371
K_i	0.0060794	0.0060860	0.75677	−0.76201

Table 5.6 Correlation coefficients for the emerging African market index ex. South Africa portfolios

MKT	SB	HL	UD	IMV	S_i	K_i	
1	-0.0153	0.0795	0.5823	-0.1531	0.0047	0.1738	MKT
	1	0.4814	0.0969	0.0959	0.056	-0.0836	SB
		1	0.1066	0.1512	0.0874	-0.0032	HL
			1	-0.1482	0.0334	0.1355	UD
				1	-0.0212	-0.0384	IMV
					1	0.1386	S_i
						1	K_i

Table 5.6 shows the correlation coefficients between the risk factors. There are no concerns about multicollinearity problems.

Figures 5.15, 5.16, 5.17, 5.18, 5.19, 5.20 and 5.21 plot the weekly values of the market factor (MKT), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the liquidity factor (IMV), skewness and kurtosis respectively.[130]

Figure 5.15 Weekly values of returns on the market index (MKT) for the emerging African market index ex. South Africa

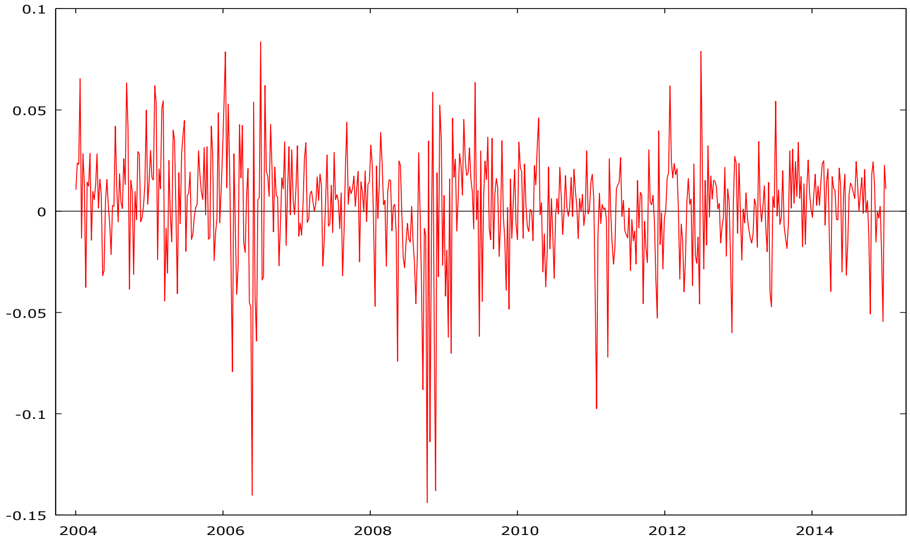
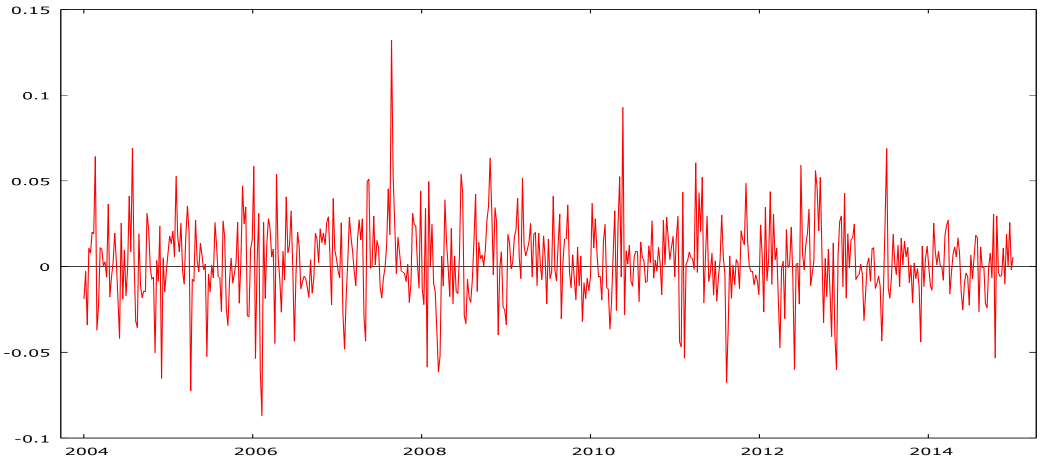


Figure 5.16 Weekly values of the returns on the portfolio formed on size (SMB) for the emerging African market index ex. South Africa



[130] The frequency distribution with the Doornik-Hansen test for normality for each variables and their correlograms are shown in the chapter appendix. The correlograms show the autocorrelation function using a maximum of 27 lags. The Ljung–Box Q-statistic is not shown but is available on request from the author.

Figure 5.17 Weekly values of the returns on the portfolio formed on value (HML) for the emerging African market index ex. South Africa

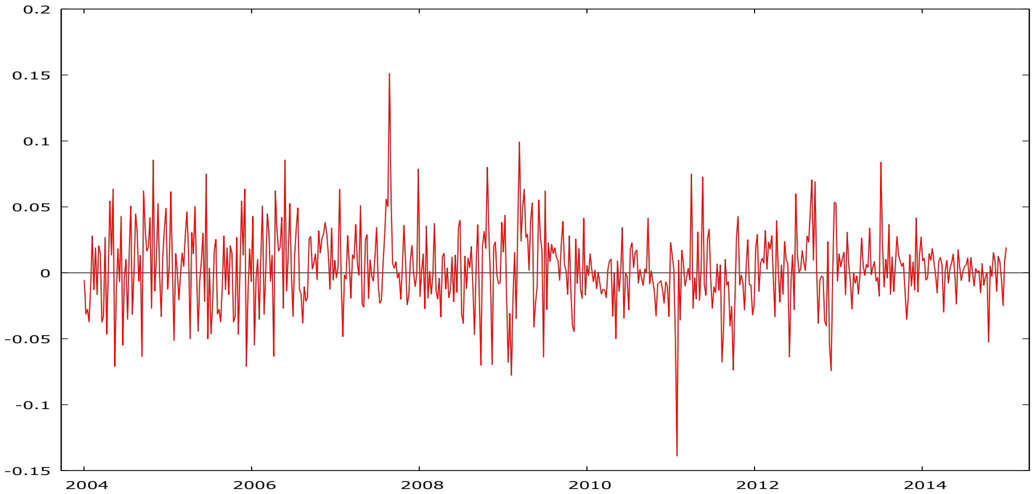


Figure 5.18 Weekly values of the returns on the portfolio formed on the momentum factor (UMD) for the emerging African market index ex. South Africa

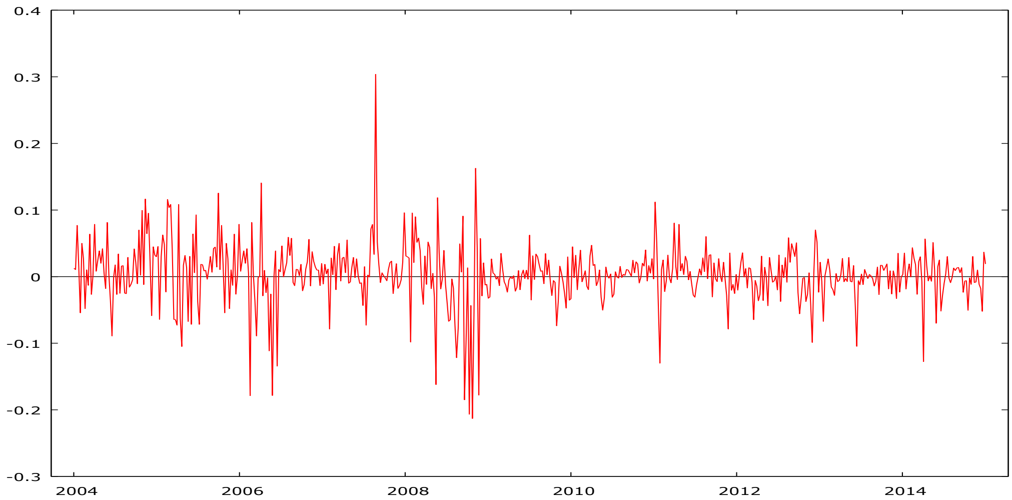


Figure 5.19 Weekly values of the returns on the portfolio formed on the liquidity factor (IMV) for the emerging African market index ex. South Africa

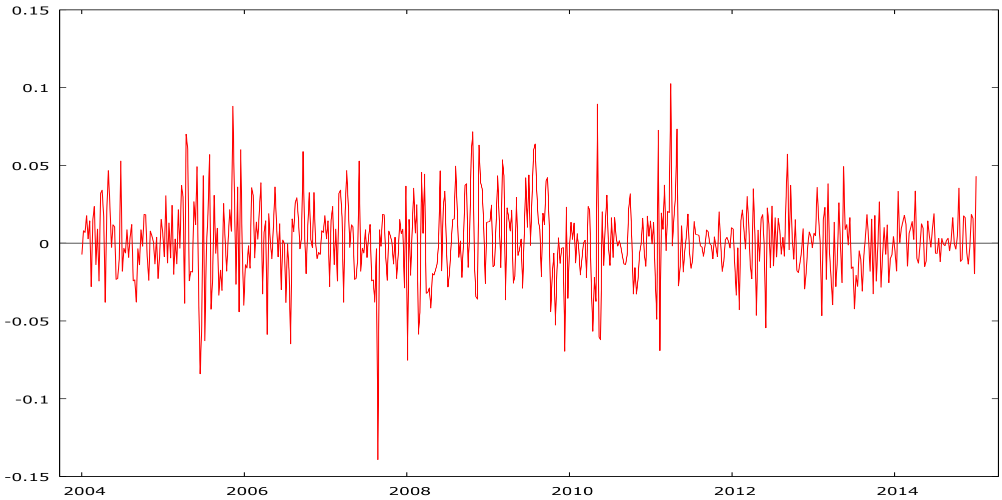


Figure 5.20 Time-series weekly skewness (S_i) values for the emerging African market index ex. South Africa

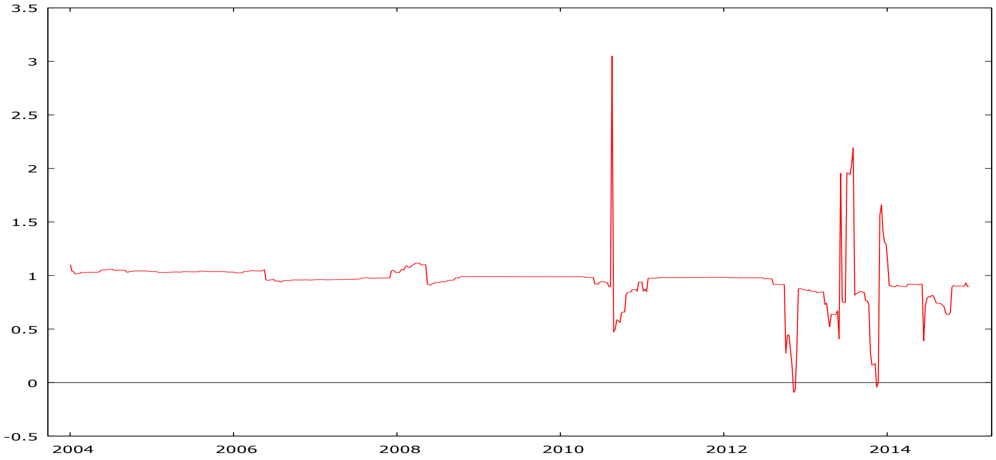


Figure 5.21 Time-series weekly kurtosis (K_i) values for the emerging African market index ex. South Africa

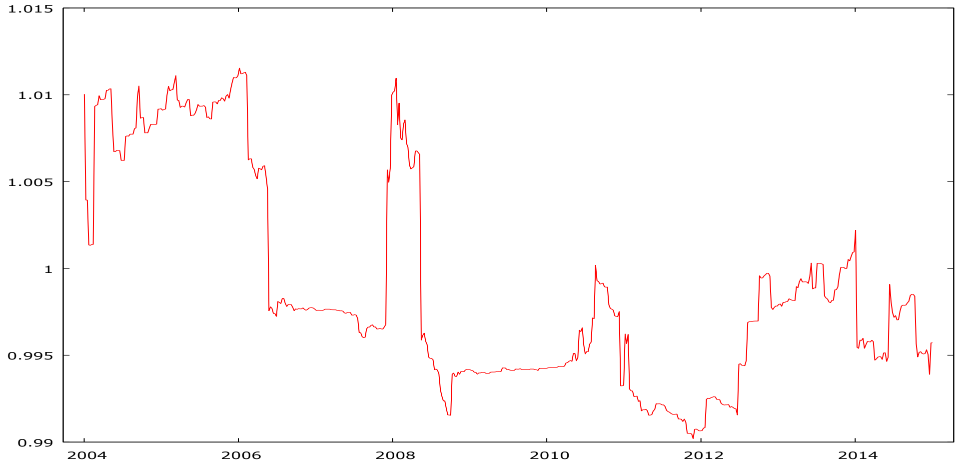


Table 5.7 Summary statistics for the frontier African market index portfolios. (full sample, 2004-2014)

Variable	Mean	Median	Minimum	Maximum
MKT	0.0021399	0.0021947	−0.054026	0.0565424
SMB	0.0039708	0	−0.195665	0.274255
HML	0.0032126	0.0029247	−0.097841	0.195405
UMD	0.0035595	0.0029572	−0.275449	0.254134
IMV	−0.0020635	−0.0020231	−0.140265	0.15331
S_i	1.06402	1.01499	-1.39765	3.92408
K_i	1.00036	1.00144	0.979476	1.01433

Variable	Std dev.	CV	Skewness	Ex. kurtosis
MKT	0.0147452	6.89057	−0.082353	2.0633
SMB	0.0483011	12.1641	0.4689	4.09269
HML	0.035563	11.0697	0.656278	2.515
UMD	0.0615406	17.2893	0.0945856	2.15467
IMV	0.0426569	20.6717	0.0699244	1.1751
S_i	0.395763	0.371952	2.97781	24.1126
K_i	0.0062028	0.0062006	−0.216729	−0.35653

Initial indications from the summary statistics in Table 5.7 show a positive weekly average return of 0.22% for the market portfolio, with a standard deviation of 1.48%, and a positive weekly average return of 0.40% on the size portfolio, with a standard deviation of 4.83%. However, the portfolio formed on value had a weekly average return of 0.32%, with a standard deviation of 3.6%. The momentum and liquidity factors had a weekly average return of 0.36% and −0.21%, respectively, with a standard deviation of 6.15% and 4.23%, respectively. The higher-order moments of skewness and kurtosis had an average weekly value of 1.06 and 1.00 respectively, with a standard deviation of 39.58% and 0.62% respectively.

Table 5.8 Correlation coefficients for the frontier African market index portfolios

MKT	SMB	HML	UMD	IMV	S_i	K_i	
1	−0.1272	0.042	0.0187	0.0925	−0.0912	−0.1517	MKT
	1	0.0967	−0.1064	0.1173	0.0168	0.0259	SMB
		1	−0.2797	0.1284	−0.1121	0.053	HML
			1	−0.1763	0.0321	0.0264	UMD
				1	−0.0805	−0.0902	IMV
					1	0.1321	S_i
						1	K_i

Table 5.8 shows the correlation between the explanatory variables. It does not detect any overly high value of the correlation coefficients that may give rise to any concerns of multicollinearity problem.

Figures 5.22, 5.23, 5.24, 5.25, 5.26, 5.27 and 5.28 plot the weekly values of the market factor (MKT), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the liquidity factor (IMV), skewness and kurtosis respectively.[131]

Figure 5.22 Weekly values of returns on the market index (MKT) for the frontier African market index

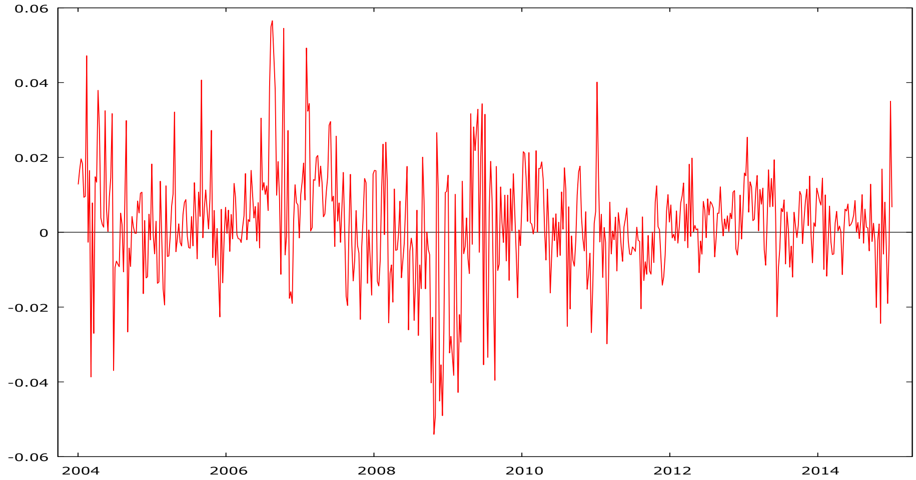
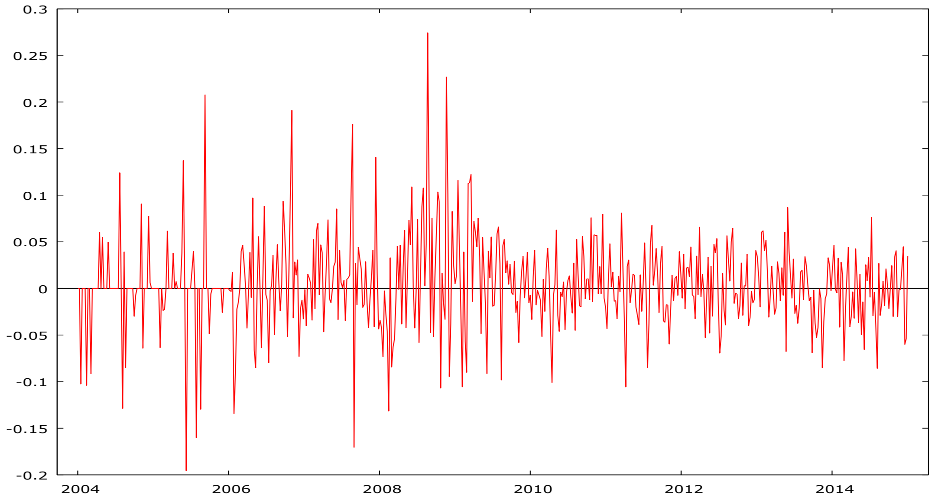


Figure 5.23 Weekly values of the returns on the portfolio formed on size (SMB) for the frontier African market index



[131] The frequency distribution with t he Doornik-Hansen test for normality for each variables and their correlograms are shown in the chapter appendix. The correlograms show the autocorrelation function using a maximum of 27 lags. The Ljung–Box Q-statistic is not shown but is available on request from the author.

Figure 5.24 Weekly values of the returns on the portfolio formed on value (HML) for the frontier African market index

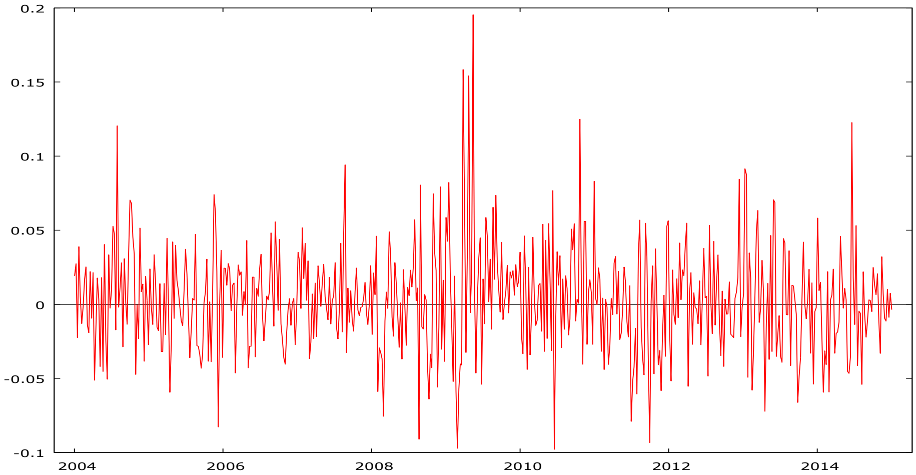


Figure 5.25 Weekly values of the returns on the portfolio formed on the momentum factor (UMD) for the frontier African market index

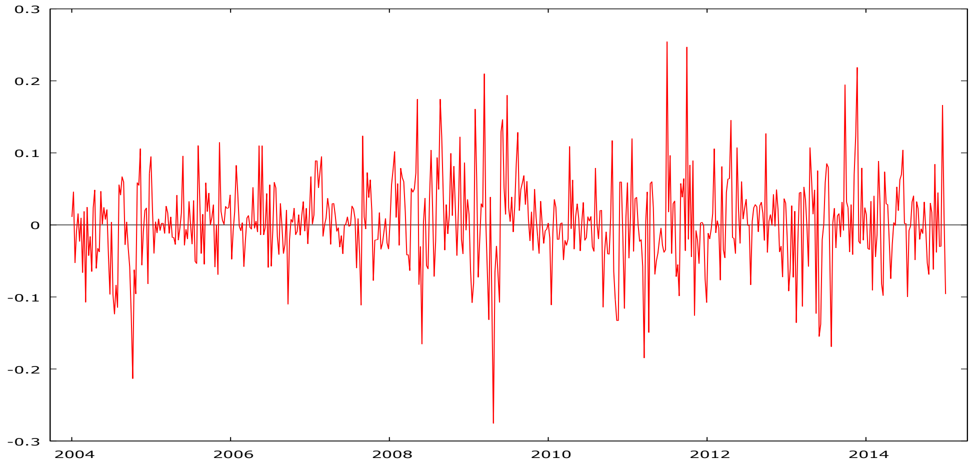


Figure 5.26 Weekly values of the returns on the portfolio formed on the liquidity factor (IMV) for the frontier African market index

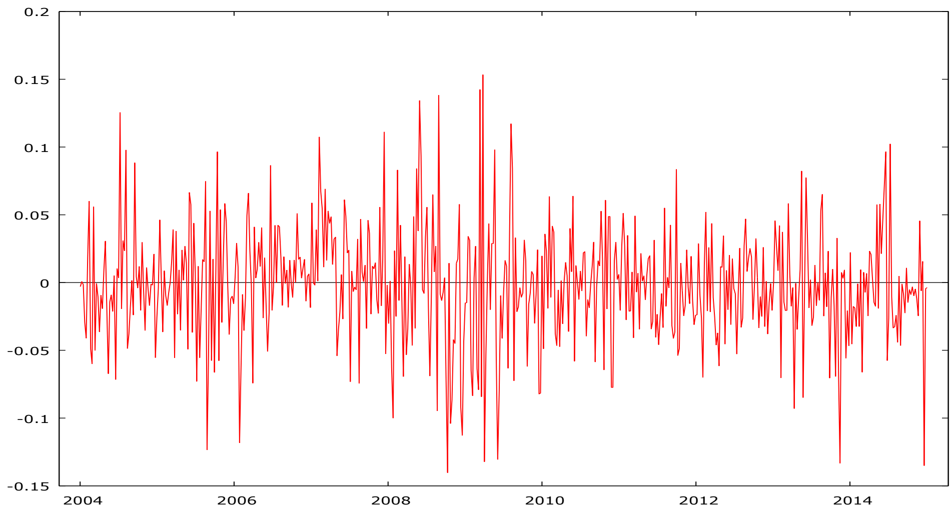


Figure 5.27 Time-series weekly skewness (S_i) values for the frontier African market index

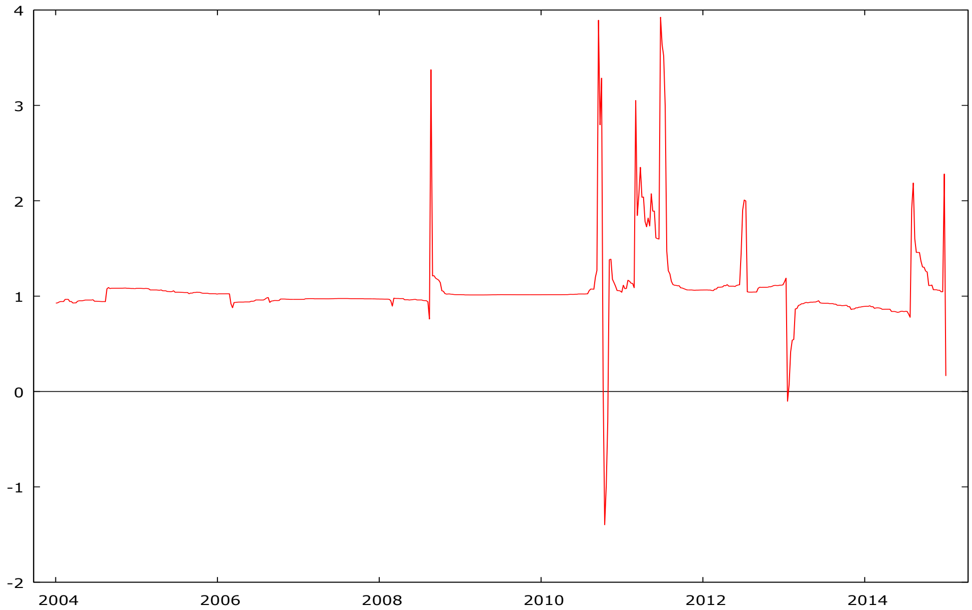
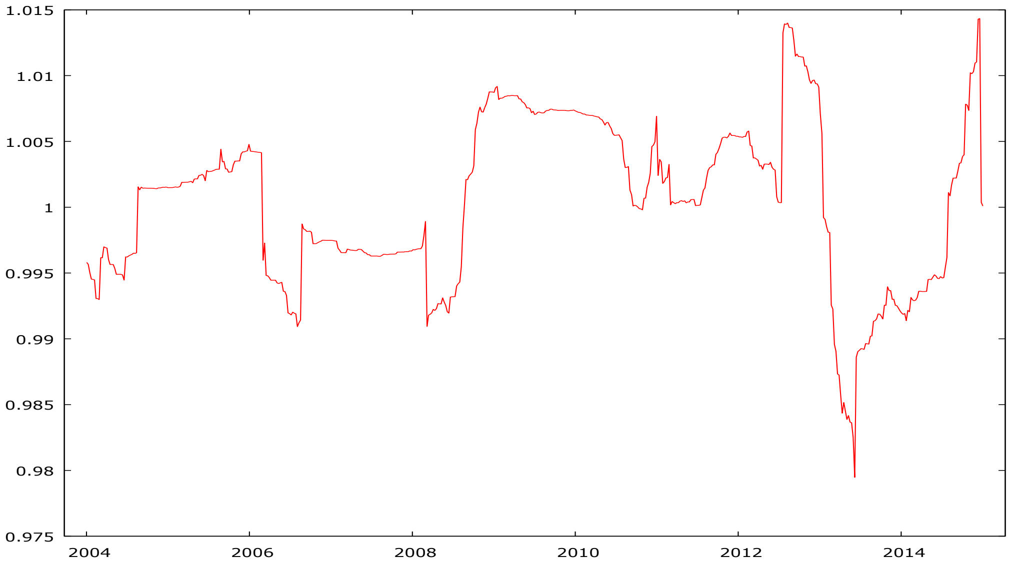


Figure 5.28 Time-series weekly kurtosis (K_i) values for the frontier African market index



5.3 Empirical findings in the South African market

This section analyses the Sharpe-Lintner CAPM, the Fama-French three-factor model and the Carhart four-factor model. It also examines the explanatory power of the liquidity factor and higher moments within the four-factor model, with adjustment for the contagion events (financial crisis period and the Arab Spring) using dummy variables. The objective of this approach is to investigate the role of the different risk factors in explaining asset pricing. The empirical results are shown in Table 5.9 where the table below shows the variable definition.

Variable	**Definition**
α_i	*Jensen alpha term (the constant term)*
β_{iM}	*Beta*
β_{is}	*factor loading on the size factor*
β_{ih}	*factor loading on the value factor*
β_{im}	*factor loading on the momentum factor*
β_{ip}	*factor loading on the liquidity factor*
S_i	*factor loading on the coskewness factor*
K_i	*factor loading on the cokurtosis factor*
Dummy_FC_AS	*dummy variable for the financial crisis and the Arab spring*

Table 5.9[132] Model performance in the South African market[133]

Coeff.	CAPM[134]	3-factor model[135]	4-factor model[136]	4-factor model + liquidity[137]	4-factor model + liquidity and contagion[138]	4-factor model + liquidity, contagion and higher moments[139]
α_i	−0.00274168** (0.00123015)	−0.00160636 (0.00113999)	−0.00166179 (0.00114502)	−0.00112217 (0.00121951)	0.000443308 (0.00126666)	0.009221 (0.0837092)
β_{iM}	1.05411*** (0.119640)	0.814259 *** (0.0819126)	0.810441*** (0.0798892)	0.782204*** (0.0833705)	0.771684*** (0.0805736)	0.771138*** (0.0791532)
β_{is}		−0.606609 *** (0.0731787)	−0.603633*** (0.0712710)	−0.413264*** (0.0769728)	−0.418064*** (0.0763046)	−0.418051*** (0.0758411)
β_{ih}		0.0525296 (0.0834949)	0.0283707 (0.0779701)	0.0180821 (0.0739083)	0.0295652 (0.0729561)	0.0300583 (0.0730565)
β_{im}			0.0407704 (0.0505914)	0.0416657 (0.0479756)	0.0360936 (0.0466760)	0.0358491 (0.0468751)
β_{ip}				−0.318495*** (0.0859401)	−0.324881*** (0.0842805)	−0.324839*** (0.0841023)
S_i						−0.000379482 (0.00110353)
K_i						−0.0084403 (0.0844355)
Dummy_FC_AS					−0.00656053*** (0.00233059)	−0.00677857*** (0.002425)
R^2 Adj R^2	0.360858 0.359743	0.550410 0.548048	0.551766 0.548620	0.574397 0.570657	0.579382 0.574939	0.579510 0.573567

[132] HAC standard errors. Data source – Reuters Eikon.
[133] *, ** and *** indicate statistical significance of the coefficient at the 10%, 5% and 1% levels
[134] $R_i - R_f = \alpha_i + \beta_{iM}(R_M) - R_f) + \varepsilon_{it}$
[135] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \varepsilon_{it}$
[136] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \varepsilon_{it}$
[137] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \varepsilon_{it}$
[138] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \delta_{iD}FCAS + \varepsilon_{it}$
[139] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \beta_{ie}S_i + \beta_{ik}K_i + \delta_{iD}FCAS + \varepsilon_{it}$

5.3.1 Performance of the CAPM against the three-factor and four-factor models in the South African market

This section focuses on investigating the role of different risk factors in explaining asset pricing using the standard CAPM, the Fama-French three-factor model, the Carhart four-factor model and their liquidity-augmented variants, within the South African basic materials index. It also investigates the role of higher-order moments in explaining realised returns and the effect of controlling for contagion events in terms of the financial crisis period and the Arab Spring.

Table 5.9 reports the results of the estimation for the standard CAPM, the three-factor and four-factor models, representing three alternative risk specifications. The explanatory power of the model increases with additional size, book-to-market value and momentum factors. This demonstrates the improved explanatory power of the Fama-French and Carhart models. The Jensen alpha terms, α_i, are negative for all three models and continue to get closer to zero with the addition of size, book-to-market factor and momentum factor. It is, however, statistically significant at the 5% level only for the Sharpe-Lintner CAPM, indicating a poor fit with established theoretical CAPM assumptions. This specifically indicates that the CAPM does not capture a significant part of the variation in the cross-section of average index returns, i.e. CAPM's univariate market beta shows little relation to variables such as size, book-to-market value, momentum and liquidity, which are strongly related to average returns.

This could be because of the naïve strategies followed by investors, which include preference for investment in highly profitable firms, overreacting to good and bad news, assuming trends in stock prices and extrapolating past growth rates too far into the future. MacKinlay (1995) notes that following these strategies, the possibility of non-zero intercept that is not solely due to missing risk factors, but also due to firm specific factors, may arise. MacKinlay (1995) also explains that since the model is developed under perfect market assumptions, the effects of market frictions and liquidity constraints are not accommodated and this may lead to non-zero intercepts in the CAPM tests.

However, the insignificant Jensen alpha terms, α_i, for the three-factor and four-factor models indicate a good fit with established theoretical assumptions, as stated in Hearn and Piesse (2009). These conform to the findings in Fama and French (1992) and Carhart (1997). These insignificant intercepts demonstrate a parsimonious description of returns and average returns. They therefore capture much of the variation in the cross-section of average returns, absorbing most of the anomalies associated with the CAPM. The three-factor model captures average returns as well as the four-factor model. Chapter 6 provides more detail on possible rationale for the deviation of the South African CAPM from CAPM theoretical assumptions.

Even with this relative poor performance of the Sharpe-Lintner CAPM compared with the Fama-French and Carhart models, many practitioners still prefer the use of the Sharpe-Lintner CAPM in estimating cost of capital. Those who document this preference include Bruner et al. (1998) and Graham and Harvey (2001).

In comparing the performance of the CAPM and the Fama-French model, Bartholdy and Peare (2005) compared the estimates of expected returns based on each model to identify the "best" possible estimate. Using a practitioner approach, they defined the best possible estimate using the R^2 (goodness of fit). R^2 measures how much the estimation procedure explains the difference in individual stock index return. Hence the best refers to the model and data that result in the highest R^2. From the results in Table 5.9, the R^2 for the Sharpe-Lintner CAPM was 36.08%, while those of the Fama-French model and the Carhart model were 55.04% and 55.17%, respectively. This suggests that the Carhart four-factor model performs best in explaining realised returns on the South Africa basic materials index. However, some precaution should be taken as to the use of the R^2, because with additional variables, the R^2 of a model will normally increase; however, the adjusted R^2 is still higher for the Carhart four-factor model (54.86%), compared to the three-factor (54.80%) and the Sharpe-Linter models (35.97%).

The estimated beta for the standard CAPM is positive and significantly different from zero at the 1% significance level, indicating that the return on the South African basic material index increases when the market risk premium increases. This behaviour is expected as identified in Sharpe (1964), Lintner (1965) and Sharpe, Alexander and Bailey (1999). When compared to the Fama-French three-factor model, the market beta remains positive and significant but the size premium is negative and statistically significant, indicating that large firms outperform small firms within the South African basic materials index. Hawawini and Keim (1995, 2000) and Hearn and Piesse (2009) also found this negative relationship.

The negative relationship between size and returns in this study can be explained by industry-specific factors within South Africa. The sizes of companies in the industry vary widely as shown in Chapter 3, with the big companies dominating the market. This reduces the revenue source for the small companies, translating into smaller profit margins compared with the large companies. According to Sadorsky (2001), the natural resources sector has remained quite volatile, complicating the business for industry players. These complications come from the capital-intensive nature of the industry as new mining projects can cost billions to build.

Secondly, industry players are dealing with depleting resource base, which pushed competitive advantage towards the ability to locate and extract low-cost, natural resources deposit to replace their depleting asset base. The products made by these companies are quite homogeneous, as product differentiation is not possible due to identical raw commodities. The best performing natural resource companies (in terms of return on investment and stock-price appreciation) are generally those companies that are the lowest cost producers, and these tend to be the large companies due to economies of scale and scope.

Other papers that assert that the size effect disappeared after the early 1980s include Eleswarapu and Reinganum (1993), Dichev (1998), Chan et al. (2000), Horowitz et al. (2000a,b), and Amihud (2002), while Martinez et al. (2005) presents evidence on the limited explanatory power of the Fama-French three-factor model. This contradicts popular findings on the effect of size on returns, which report that small firms outperform big firms as observed in Banz (1981) and Fama and French (1992, 1996). Others who present evidence on the size effect in the US include Reinganum (1981), Keim (1983), Brown et al. (1983) and Lamoureux and Sanger (1989). International studies that find evidence of a size effect include Heston et al. (1999), Barry et al. (2002), Chan et al. (1991) and Annaert et al. (2002). However, these studies mostly focus on the developed markets.

The value factor is positive and statistically insignificant. This is contradictory to the findings of Fama and French (1992, 1996), who find a significant relationship between book-to-market value and returns. Loughran (1997) insists that there is no consistent relationship between book-to-market value and realised return. Other authors have proffered some explanation for the value premium in Fama and French (1992, 1993), with Black (1993) suggesting that the value premium was due to data-snooping, and this is supported by MacKinaly (1995). Kothari et al. (1995) argue that value premium is due to survivorship bias, while Lakonishok et al. (1994) insist that it results from investor overreaction.

In the Carhart four-factor model, the market beta remains positive and significant while the size also remains negative and significant. There also does not appear to be any value premium as the book-to-market value factor was found to be insignificant. This is consistent with the findings of Wang and Xu (2004) and Shum and Tang (2005) in the Asian market and the assertions in Gaunt (2004) using Australian data. There is a lack of empirical evidence on whether the value premium is present in emerging equity markets generally, and particularly in the emerging African stock markets, as stated in Bundoo (2008).

There is no momentum premium within the South African basic material index, with the momentum factor being positive, but this is contrary to findings in Jegadeesh and Titman (1993), Carhart (1997), Liew and Vassalou (2000) and L'Her, Masmoudi and Suret (2004). Unlike the findings in this study, momentum has also been found to be significant in the Asian market (Rouwenhorst, 1998, and Chui et al., 2000) and in the emerging markets (Rouwenhorst, 1999). However, the sources of momentum have remained contentious, with Conrad and Kaul (1998) and Bulkley and Nawosah (2009) insisting that momentum is mainly explained by risk. However, Jegadeesh and Titman (2002) and Bhoota (2011) found that momentum largely results from behavioural biases. Another explanation comes from Lo and MacKinlay (1990), who suggest that the sources of momentum profits are positive serial correlation (negative cross-sectional correlation) and dispersion in unconditional mean returns. This will be discussed in greater detail in relation to the emerging and frontier African markets in Sections 5.4 and 5.6.

5.3.2 Liquidity-adjusted four-factor model in the South African market

With the introduction of the liquidity factor, the market beta and size remained significant while the value and momentum factors remained insignificant. This corresponds to the findings of Bundoo (2008) on the relative unimportance of the value factor. He highlights that there is a lack of empirical evidence of whether the value premium is present in emerging equity markets generally, and particularly in the emerging African stock markets. Hence I can conclude that accounting for beta and size factors eliminates the relevance of the value and momentum factor in asset pricing within the South African market.

The liquidity factor is significant but has a negative relationship with returns, which is in contrast to the findings in Amihud and Mendelson (1986), Pástor and Stambaugh (2003) and Chordia et al. (2000). A recent study by Lam and Tam (2011) shows that liquidity continues to be an important factor even after accounting for other well-established risk factors. Lee (2011) supports this view, revealing that liquidity is priced after controlling for market risk, size and value. However, as stated in Lischewski and Voronkova (2012), a number of studies have examined the relevance of liquidity in asset pricing, producing conflicting results.

Hearn (2011) identified that the effect of liquidity on asset pricing depends on the structure of the surveyed stock market. The study finds evidence of size and liquidity being priced in in Morocco, whereas the results for other north African countries were mixed. This will seem to be the case for the liquidity discount found in this study, which is somewhat related to the size discount as the larger companies tend to be the most liquid in the African market. This could be driven by larger capital-raising opportunities available to large companies in these markets, resulting from high interest of foreign investors in large stocks, lower-cost, international financing and/or availability of domestic government-subsidised credit.

Similar findings are reported in Claessens and Dasgupta (1995), who investigated 19 emerging markets. They disclose that the contradictory behaviour of these emerging markets may be due to tax systems, market microstructure, improvements in market structures and the opening of markets to foreign investors. Further evidences of this negative relationship are reported in Amihud, Mendelson and Wood (1990) and Amihud (2002). The liquidity-adjusted models fare better in term of goodness of fit, R^2, for cross-sectional returns, and they also fare better in terms of p-values in specification tests.

5.3.3 Effect of contagion on the liquidity-adjusted four-factor model in the South African market

When the dummy variable for the shock events (the financial crisis and the Arab Spring) was included, the results for the other variables remained the same as when the model does not contain the contagion dummy. However, the contagion dummy was significant at 1%, highlighting the importance of accounting for time variation. The Jensen alpha term for both the liquidity-augmented four-factor model and the liquidity and higher-moments augmented four-factor model became positive, although still insignificant.

The direction of the alpha term is important, given that the direction of the alpha terms before the inclusion of the contagion dummy has been negative. This highlights the impact of contagion on returns on the South African basic materials index. This is also supported by the negative sign on the contagion dummy. Although this is expected as the 2008 financial crisis and the Arab Spring had negative impact of returns, the entire negative direction of the alpha term can be entirely attributed to the contagion dummy. This highlights the importance of accounting for time variation in assessing portfolio performance within the South African market.

The impact on the adjusted R^2 is also important as we observe an increase from 57.07% to 57.49% between the liquidity-augmented four-factor model and the same model that includes the contagion dummy. This indicates that the contagion dummy improves the overall performance of the model compared to the models that do not account for the effect of contagion.

I therefore conclude that the shock events have had a time-varying effect on the models. Indeed, time variation is known to affect many financial and macroeconomic variables, as identified in Pettenuzzo and Timmermann (2005). Further evaluation of the effect of this shock on the estimates of asset-pricing models and the importance of accounting for time variation in the asset-pricing model using a conditional asset-pricing methodology, will be discussed in Chapter 7.

5.3.4 Higher-moment CAPM in the South African market

The results show that the higher moments of returns distribution are not priced in the South African basic materials index. This supports the findings in Hung (2008), indicating that skewness does not explain return variation. Friend and Westfield (1980) investigated the explanatory power of skewness in the US security markets and found that, contrary to the conclusions of Kraus and Litzenberger (1976), investors do not pay a premium for positive skewness of portfolio returns.

According to DeMiguel and Nogales (2007) and Hung (2008), this may be due to parameter uncertainty resulting from the use of observed information in estimating unknown parameters, and also due to unstable predictive relations and time variation as identified in Lewis (2006) and Paye and Timmermann (2006). This is supported by Bekaert et al. (1998), who highlight that the skewness and kurtosis present in emerging market returns change over time. Sanchez-Torres and Sentana (1998) showed no evidence of preference for positive skewness by investors using the Spanish stock market.

Singleton and Wingender (1986) and Peiro (1999) insist that despite evidence that the coskewness and cokurtosis risk in asset return are priced, fundamental questions remain as to how these studies confirm the existence of higher moments of return distributions. They also point to the possibility of incorrect assumptions resulting in the observed skewness asymmetry in returns. Chiao, Hung and Srivastava (2003) question the ability of higher moments of return distribution to persist through time. Singleton and Wingender (1986) thus show that higher moments of return distribution do not persist through time even with the presence of a stable frequency of positive skewness in most individual stock and portfolio returns.

Investigating the Taiwanese market between 1974 and 1998, Chiao, Hung and Srivastava (2003) found no apparent relationship between higher moments and returns. They provide three plausible explanations for this. The first, which could also apply to the South African basic materials index, is the collinearity between the covariance, coskewness and/or cokurtosis risk measures. As identified in Friend and Westerfield (1980), this could be a potential problem. The second explanation results from the frequent revision of strategy by investors, which limits the ability of higher moments to explain returns distribution to a negligible level.

This may result from transaction costs being incurred due to frequent trading, which will blur the contributions of higher moments. This is demonstrated within the South African market, where I find an increasing trend for turnover of stocks (See Figure 1.7 in Chapter 1, for the South African market). According to Samuelson (1970), expected return and variance become very important and beyond the variance, all other moments become of relatively much smaller importance. This is what I find within the South African market: significant beta and insignificant higher moments.

The third point that may also apply to the South African basic materials index is that the relationship between risk and return is not indicated directly by applying ex-post realisation as a proxy for ex-ante expectations, as observed in the unconditional CAPM of Pettengill et al. (1995). Chiao, Hung and Srivastava (2003) highlight that this is particularly significant when the realised market return is less than the risk-free rate. I do not expect this to be much of a problem as the measure of risk-free rate used (see Section 3.3 in Chapter 3) ensures that the market returns are higher, hence true risk-free returns.

Compared to the four-factor model that accounts for liquidity and contagion, the alpha term for the model that includes higher moments is still insignificant, but the adjusted R^2 is lower at 57.36%, hence the four-factor model that accounts for liquidity and contagion performs best in the South African market.

5.4 Empirical findings in the emerging African market

As in the South African market, the objective of this section is to investigate the role of the different risk factors in explaining asset pricing within the emerging African market index. The empirical results are shown in Table 5.10.

Table 5.10[140] Model performance for the emerging African market[141]

Coeff.	CAPM[142]	3-factor model[143]	4-factor model[144]	4-factor model + liquidity[145]	4-factor model + liquidity and contagion[146]	4-factor model + liquidity, contagion and higher moments[147]
α_i	−0.00153846* (0.000946723)	−0.00166722* (0.000909299)	−0.00169653* (0.000907255)	−0.00170952* (0.000907358)	−0.000350224 (0.000940420)	−0.192618** (0.0863075)
β_{iM}	0.788427*** (0.0677367)	0.803047*** (0.0644096)	0.797338*** (0.0628137)	0.790198*** (0.0654904)	0.775882*** (0.0629981)	0.766978*** (0.0645285)
β_{is}		0.0763167* (0.0417691)	0.0706369* (0.0425021)	0.0911008** (0.0439646)	0.0913560** (0.0428271)	0.0959405** (0.0428184)
β_{ih}		−0.0803463 (0.0611953)	−0.0574970 (0.0621561)	−0.0626380 (0.0622812)	−0.0758104 (0.0631049)	−0.0835243 (0.061927)
β_{im}			0.0359296 (0.0343935)	0.0341063 (0.0338087)	0.0306662 (0.0333789)	0.0287265 (0.0329108)
β_{ip}				−0.0351032 (0.0436339)	−0.0407794 (0.0423631)	−0.0427367 (0.0424116)
S_i						−0.000274863 (0.00057182)
K_i						0.193561** (0.0870456)
Dummy_FC_AS					−0.00562245*** (0.00195754)	−0.00239083 (0.00228456)
R^2 Adj R^2	0.379077 0.377993	0.387239 0.384019	0.389383 0.385098	0.390404 0.385047	0.399804 0.393464	0.406626 0.398239

140 HAC standard errors. Data source – Reuters Eikon.

141 T = 575. *, ** and *** indicates statistical significance of the coefficient at the 10%, 5% and 1% levels.

142 $R_i - R_f = \alpha_i + \beta_{iM}(R_M) - R_f) + \varepsilon_{it}$

143 $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \varepsilon_{it}$

144 $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \varepsilon_{it}$

145 145 $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \varepsilon_{it}$

146 146 $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \delta_{iD}FCAS + \varepsilon_{it}$

147 $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \beta_{ie}S_i + \beta_{ik}K_i + \delta_{iD}FCAS + \varepsilon_{it}$

5.4.1 Performance of the CAPM against the three-factor and four-factor models in the emerging African market

This section focuses on investigating the role of different risk factors in explaining asset pricing using the standard CAPM, the Fama-French three-factor model, the Carhart four-factor model and the liquidity-adjusted four-factor model, within the emerging African basic materials index. It also investigates the role of higher-order moments in explaining realised returns and the effect of controlling for contagion events in terms of the financial crisis period and the Arab Spring.

Table 5.10 reports the results of the estimation for the standard CAPM, the three-factor and the four-factor models, representing three alternative risk specifications. Much like in the South African market, the explanatory power of the model increases with additional size, book-to-market value and momentum factors. This is an indication of the improved explanatory power of the Fama-French and Carhart models. The Jensen alpha terms, α_i, are negative for all three models and continue to get closer to zero with the addition of size, book-to-market factor and momentum factor. They were, however, statistically significant for all three models, indicating a poor fit with established theoretical CAPM assumptions. This is contrary to findings in Hearn and Piesse (2009), who identified that Jensen alpha terms are not statistically significant within the African market.

The explanation for this significant alpha could be traced to investment strategies in these markets through preference for investment in highly profitable firms, overreacting to good and bad news, assuming trends in stock prices and extrapolating past growth rates too far into the future, as also seen within the South African market. These are aided by poor information dissemination and a relatively underdeveloped institutional environment within which the financial markets operate, when compared to South Africa and the developed markets. Another important factor that will be more pronounced within this market is the effect of time variation resulting from macroeconomic factors.

This significant alpha may also be due to missing risk factor; however, MacKinlay (1995) identified that non-zero intercepts may not be solely due to missing risk factors, but may be due to firm/index specific factors. He identified the possible impact of market friction and liquidity constraints on intercepts of CAPM tests. Conrad and Kaul (1993) consider the possibility that biases in computed returns explain the deviations. They note that the implicit portfolio rebalancing in most analysis biases measured returns upwards, leading to overstating returns and CAPM deviations. This reflects the impact of survivorship bias, and this has been eliminated from this dataset.

The performance of the model can also be seen in the goodness of fit (R^2) of the models. As shown on Table 5.10, the R^2 for the Sharpe-Lintner CAPM was 37.91%, while those of the Fama-French model and the Carhart model were 38.72% and 38.94%, respectively. This suggests that the Carhart four-factor model performs marginally better in explaining realised returns on the South Africa basic materials index. However, some precaution should be taken as to the use of the R^2, because with additional variables the R^2 will normally increase; however, the adjusted R^2 is still highest for the Carhart four-factor model (38.51%), compared to the three-factor (38.40%) and the Sharpe-Lintner models (37.80%).

The CAPM beta was positive and significant at the 1% level and this conforms to theoretical predictions as stated in Sharpe (1964), Lintner (1965) and Sharpe, Alexander and Bailey (1999). Using the Fama-French three-factor model, I find that beta and size are significant in the emerging African market. Beta is positive and significant at the 1% level, while size is positive and significant at the 10% level. This size effect demonstrates that small firms outperform larger firms in these markets.

The diversification advantage of the index has resulted in a positive size effect. This is obvious given the negative factor loading for the size variable within the South African market and, as will be seen later, within the emerging African market excluding South Africa. This has also exacerbated the potential impact of time variation, as the potential effect of external shocks will increase within the index. As seen in Malkiel and Xu (1997, 2004), the impact of idiosyncratic risk, which they relate to size risk, will also be more pronounced, as the characteristics of the markets that make up the index will be reflected on the index. The markets within the emerging African market are homogeneous enough to be classed within the index, but still remain heterogeneous enough to provide some diversification advantages, hence the impact on the size factor. This is also supported by the market beta value when compared with the South African market beta, where beta is higher.

Following the survey in van Dijk (2011), other studies that found a positive relationship include Banz (1981), Brown et al. (1983), Lamoureux and Sanger (1989) and Fama and French (1992), but these were in the US market. A broad range of international studies reported in van Dijk (2011) suggest that size effect is positive in most developed and emerging markets; see Gillan (1990), Annaert et al. (2002) and Aksu and Onder (2003). Those who found the size effect in the African market include van Rensburg and Robertson (2003) and Basiewicz and Auret (2009).

The value factor is negative and statistically insignificant. The direction of the value factor is contradictory to the findings of Fama and French (1992, 1996), who find a positive and significant relationship between book-to-market value and expected returns. However, Bossaerts and Fohlin (2000) also found a negative value effect in their study of German stocks. The insignificant value factor within the emerging African market is likely due to investors' aversion of a probable "value trap" due to treatment of depreciation, loans, liens and intangibles within the book value.

Controversy still exists over the importance of value in explaining returns. Loughran (1997) insists that there is no consistent relationship between book-to-market value and realised return. Other authors have proffered some explanation for the value premium in Fama and French (1992, 1993), with Black (1993) suggesting that the value premium was due to data-snooping; this is supported by MacKinlay (1995). Kothari et al. (1995) argue that value premium is due to survivorship bias, while Lakonishok et al. (1994) insist that it results from investor overreaction.

Overall, the insignificant value factor is consistent with the findings of Wang and Xu (2004) and Shum and Tang (2005) in the Asian market, and the assertions in Gaunt (2004) using Australian data. There is a lack of empirical evidence on whether the value premium is present in emerging equity markets generally, and particularly in the emerging African stock markets, as stated in Bundoo (2008).

The momentum factor in the emerging Africa index is also not significant. This contradicts the finding in Jegadeesh and Titman (1993), Carhart (1997), Chan, Hamao and Lakonishok (1991), Griffin, Ji and Martin (2003), Asness, Moskowitz and Pedersen (2013) and Chui, Titman and Wei (2010). However, Rouwenhorst (1999) indicates that it is quite difficult to detect momentum in emerging market countries, where he found significant momentum profit in six out of 20 emerging markets in his sample. This he attributed to the highly volatile nature of emerging market returns. Rouwenhorst (1999) insists that given the high trading costs, the existing evidence does not support the presence of momentum returns in emerging markets. I can attribute the insignificant momentum factor in the emerging African markets to the impact of the South African market. This is because given the slow pace of information flow in the African market and the gradual response of stock prices to earnings news, I expect the momentum factor to be significant. I hence attribute this insignificance to the comparative efficiency of the South African market and its effect within the emerging African index.

The source of this momentum return has, however, remained controversial, with Conrad and Kaul (1998) and Bulkey and Nawosah (2009) insisting that momentum is mainly explained by risk. Lo and Mackinley (1990) suggest that the sources of momentum returns are positive serial correlation (negative cross-sectional correlation) and dispersion in unconditional mean returns.

5.4.2 Liquidity-adjusted four-factor model in the emerging African market

Table 5.10 shows that liquidity is not priced in the four-factor model within the emerging African market. The importance of the other variables remained the same, with the Jensen alpha term also significant. The adjusted R^2 indicates that the model that includes the liquidity measure performs poorly within the emerging African market, with an adjusted R^2 of 38.505%, compared to 38.510% for the four-factor model. This is quite interesting, given the illiquidity and thin trading problems that characterise the African market. However, when we compare the results to those within the South African market, it becomes obvious that the interaction between the different markets within the emerging African market has reduced the importance of liquidity. The inclusion of the liquidity factor only served to increase the premiums associated with size, but reduced that associated with the market beta. This suggests that liquidity is reflected in the size of the companies sampled within the emerging African market. This is contrary to the findings in Lee (2011), who insists that liquidity is priced after controlling for market risk, size effect and value effect.

Other contradictory results have also been found on the relevance of liquidity, as stated in Lischewski and Voronkova (2012). However, Hearn (2011) insists that the effect of liquidity on asset pricing depends on the structure of the surveyed stock market. He finds evidence of size and liquidity being priced in Morocco, but not in other north African countries. Lesmond (2005) highlights that his bid-ask measure of liquidity remains the most demonstrable indicator of overall liquidity, as also noted in Jain (2002). Lee (1993) continues to insist that there are deficiencies in the application of any bid-ask construct.

The concept of liquidity itself has remained quite difficult to define because its characteristics transcend a number of transactional properties of markets, as reported by Hearn (2011). Lesmond (2005) identifies some of these transactional properties as resiliency, depth and tightness, while O’Hara (2003) includes information. As identified, the plausible reason for the insignificant liquidity factor is the composition of the index, in terms of the South African, Egyptian, Moroccan stocks being together within the portfolio. There may be an offsetting effect on some of the variables; this will be analysed further in the discussion chapter.

5.4.3 Effect of contagion on liquidity-augmented four-factor model in the emerging African market

The exogenous shock identified in the dummy variable in Table 5.10 relates to the financial crisis and the Arab Spring. The result indicates that these exogenous shocks had a profound effect on the model. The findings show that the dummy variable was negative and significant at the 1% level, with the alpha terms being insignificant. This highlights the importance of accounting for time variations in estimates of the CAPM, thereby refuting the commonly made assumption that beta remains constant over time. Unlike the findings in the South African market, I find that accounting for the contagion variable does not change the sign on the alpha term, indicating that although not significant, the emerging African market has a tendency to perform worse than the South African market.

Following Jagannathan and Wang (1996), the implication of the contagion dummy could relate to the impact of business cycles. Business cycles will usually present variations in performance, which is likely due to varying firm cash flow and the degree of a firm’s financial leverage, hence the possibility of a varying relative risk. In theory, this implies that the models can hold conditionally on time information, period by period, even when the unconditional CAPM does not hold.

The indications are that this contagion factor is due to systematic stochastic changes affecting the environment that generates returns, as also observed in Chan and Lakonishok (1993), Black (1993) and Jagannathan and Wang (1996). According to Harvey (1994), emerging markets are mostly influenced by local information sets rather than global information sets. This is because most emerging and African markets are segmented from the world capital markets, as identified in Kim and Singal (2000), Bekaert and Harvey (2000) and Bekaert (1995); hence the implicit assumption that the world capital markets are completely integrated does not hold. This does not, however, mean complete segmentation either, hence shocks from developed markets can still affect the emerging African market. This is quite obvious from the financial crisis and Arab Spring contagion, as it shows that shocks can affect partially segmented markets. Harvey

(1994) also identified that risk loadings in emerging markets are not constant, as suggested by many researchers in developed markets, as they are time-varying in emerging markets.

We also observe that when higher moments are included in the liquidity-augmented four-factor model, the contagion dummy becomes irrelevant. However, the alpha term becomes significant, indicating that the model does not perform well in explaining realised returns.

5.4.4 Higher-moment CAPM in the emerging African market

The results for the liquidity- and higher-moments augmented four-factor model show that coskewness is not priced in the emerging African market, while the cokurtosis is priced. The contagion dummy becomes insignificant, indicating that the higher-order moments reduce the importance of time variation within the model. However, the Jensen alpha term is significant, which indicates that the model does not perform well in explaining the returns behaviour within the emerging African market.

The results for the skewness and kurtosis factors are consistent with the findings in Friend and Westfield (1980) and Hung (2008), who find that investors do not pay a premium for positive skewness of portfolio returns, but find that kurtosis provides some explanation of expected returns. Sanchez-Torres and Sentana (1998) showed no evidence of preference for positive skewness by investors using the Spanish stock market, while Fang and Lai (1997) find evidence for the pricing of cokurtosis in the US market. Other researchers that investigated the effect of skewness and kurtosis include Faff and Chan (1998) and Adock and Shutes (2005).

However, the importance of higher moments is in question here, as the alpha term indicates that the SMB, HML, UMD, IMV loadings in the presence of the contagion dummy provide such good proxies for the higher-order moments and hence are more superior in actual use. This conclusion has also been reached in Chung, Johnson and Schill (2004). Many others have doubts as to the importance of higher moments. Singleton and Wingender (1986) and Peiro (1999) insist that despite evidence that the coskewness and cokurtosis risks in asset return are priced, fundamental questions remain as to how these studies confirm the existence of higher moments of return distributions. They also point to the possibility of incorrect assumptions resulting in the observed skewness asymmetry in returns. Chiao, Hung and Srivastava (2003) question the ability of higher moments of return distribution to persist through time. Singleton and Wingender (1986) thus show that higher moments of return distribution do not persist through time even with the presence of a stable frequency of positive skewness in most individual stock and portfolio returns.

They provide three plausible explanations for this. The first is the collinearity between the covariance, coskewness and cokurtosis risk measures. As identified in Friend and Westerfield (1980), this could be a potential problem. The second explanation results from the frequent revision of strategy by investors, which limits the ability of higher moments to explain returns distribution to a negligible level. This may result from transaction costs being incurred due to frequent trading, which may blur the contributions of higher moments. According to Samuelson (1970), expected return and variance become very important and beyond the variance all other moments become relatively of much smaller importance. The third point is that the relationship between beta and return is not indicated directly by applying ex-post realisation and proxy for ex-ante expectations, as observed by the unconditional CAPM of Pettengill et al. (1995).

As identified in Barberis (2000), the parameters of these models are typically estimated with considerable uncertainty and, according to Pettenuzzo and Timmermann (2005), one aspect that receives less attention is model instability. This supports the long-lasting view in finance that suggests that the probability of return distribution changes over time, leading practitioners and academics to rely on more recent data, as identified in Pástor and Stambaugh (2001). Further analysis of the importance of higher-order moments will be made using a conditional CAPM-type model in Chapter 7.

Due to the significant difference between the findings within the South African market compared to the emerging African market that includes South Africa, a further analysis of the risk-return relationship within the emerging African market excluding South Africa will be made.

5.5 Empirical findings in the emerging African market excluding South Africa

As in the South African market and the emerging African market, the objective of this section is to investigate the role of the different risk factors in explaining asset pricing within the emerging African market excluding South Africa index. The empirical results are shown in Table 5.11.

Table 5.11[148] Model performance for the emerging African market excluding South Africa [149]

Coeff.	CAPM[150]	3-factor model[151]	4-factor model[152]	4-factor model + liquidity[153]	4-factor model + liquidity and contagion[154]	4-factor model + liquidity, contagion and higher moments[155]
α_i	−0.000303961 (0.000936634)	−5.85330e-05 (0.000903146)	−0.000131749 (0.000825323)	−0.000226469 (0.000818697)	0.000673819 (0.000895996)	−0.370386** (0.167989)
β_{iM}	0.773389*** (0.0380698)	0.763495*** (0.0373764)	0.570914*** (0.0463033)	0.577538*** (0.0457881)	0.570192*** (0.0458402)	0.563816*** (0.0457841)
β_{is}		−0.175687*** (0.0491774)	−0.212918*** (0.0480996)	−0.215075*** (0.0466551)	−0.209831*** (0.0457877)	−0.203346*** (0.0446733)
β_{ih}		0.0873957* (0.0446112)	0.0836887** (0.0395328)	0.0742680* (0.0391656)	0.0712296* (0.0380578)	0.0676494* (0.037291)
β_{im}			0.197877*** (0.0315364)	0.202097*** (0.0300815)	0.201803*** (0.0300931)	0.198446*** (0.0292625)
β_{ip}				0.0682631** (0.0314736)	0.0723881** (0.0315716)	0.0709348** (0.0318461)
S_i						0.000808879 (0.00356724)
K_i						0.370089** (0.168695)
Dummy_FC_AS					−0.00389571** (0.00168830)	−0.00119112 (0.00179115)
R^2 Adj R^2	0.536787 0.535979	0.553792 0.551448	0.617450 0.614765	0.621020 0.617690	0.624217 0.620247	0.628757 0.623510

[148] HAC standard errors. Data source – Reuters Eikon.

[149] T = 575. *, ** and *** indicate statistical significance of the coefficient at the 10%, 5% and 1% levels.

[150] $R_i - R_f = \alpha_i + \beta_{iM}(R_M) - R_f) + \varepsilon_{it}$

[151] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \varepsilon_{it}$

[152] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \varepsilon_{it}$

[153] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \varepsilon_{it}$

[154] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \delta_{iD}FCAS + \varepsilon_{it}$

[155] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \beta_{ie}S_i + \beta_{ik}K_i + \delta_{iD}FCAS + \varepsilon_{it}$

5.5.1 The performance of the CAPM against the three-factor and four-factor models in the emerging African market excluding South Africa

The Jensen alpha terms are insignificant for all models, excluding the liquidity and higher-moment adjusted four-factor model that accounts for the contagion effect. The insignificant alpha indicates a good fit with theoretical assumptions for the CAPM, the three-factor model, the four-factor model, the liquidity-augmented four-factor model and the contagion and liquidity-augmented four-factor model. This is in line with the Hearn and Piesse (2009), who point out that within Africa, the Jensen alpha terms are not statistically significant. The goodness of fit of the models increases with additional size, book-to-market value, momentum, liquidity, contagion and higher-moment factors. This demonstrates the improved explanatory power of the multifactor models.

AS demonstrated by the Jensen alpha term α_i, the models clearly performed better in the emerging African market excluding South Africa than in the emerging African market. This could be due to the varying levels of integration with developed markets, as stated in Stulz (1999). When integration is achieved, Koedijk and Dijk (2004) point out that the sensitivity of a stock return to its home country index also captures the stock's sensitivity to global risk factors. Hence when segmented, the sensitivity does not entirely capture the sensitivity to global risk factors. This relates to the fact that the South African market remains the most integrated of the African markets, hence the varying sensitivity to global risk factors when compared to other African markets within the emerging African market. Also, the characteristics of the South African market differ from those of Egypt and Morocco in terms of levels and impact of political instability, religious background, market development, investor protection and legal system. The impact of legal systems is analysed in detail in La Porta et al. (1997).[156]

In regards to the coefficients, Table 5.11 indicates the importance of beta, size, book-to-market value, momentum and liquidity in explaining realised returns in the emerging African market excluding South Africa. However, the size factor does not conform to the expectations of Fama and French (1993), as there is no premium on the stock of small firms. The value factor is significant at the 10% level, which is contradictory to the findings in our emerging African market sample. The factor loading for value is positive, which is again contradictory to the

[156] La Porta et al. (1997), *Legal determinants of external finance*.

findings in our emerging African market sample, although the value factor there was insignificant.

This can be explained using the growth potential of the emerging African market excluding South Africa, as the factor loadings on HML are important for describing the returns on growth-stock funds. This corroborates the findings in Fama and French (1996). This may also imply that the basic materials sector within the emerging African market excluding South Africa is distressed, as distressed industries have higher loading on HML. Fama and French (1993) highlight that average HML return is a premium for a state-variable risk related to relative distress. High book-to-market value is associated with persistently low earnings, while a low book-to-market value is typical of firms that have persistently strong earnings. However, Fama and French (1994) argue that loadings of industries on HML will vary with the business cycle, as strong positive HML is related to bad economic times while negative loadings are consistent with good economic times. I, however, find that when I control for potential bad economic times in the contagion dummy, the factor loading on the HML remained positive. This indicates a likely persistence of the HML factor loading through business cycles. This I relate to the composition of companies within the basic materials sector, with the larger firms dominating the sector.

The momentum factor indicates a momentum premium within the emerging African market excluding South Africa. One reason for this momentum premium is the slow pace of information flow in the African market and the gradual response of stock prices to earnings news; hence I expect the momentum factor to be significant. This is particularly so in less-efficient parts of the African market, as I see momentum premium when the South African market data is not included in the emerging Africa index. Behavioural biases can result in momentum profits, as stated in Jegadeesh and Titman (2002) and Bhootra (2011). This is also particularly a source of momentum in less-efficient markets, as identified in Section 2.2.6 of Chapter 2. The impact of behavioural biases on momentum returns within the African indices will be discussed in detail in Chapter 6.

The liquidity factor is positive and significant, indicating that illiquid firms outperform liquid firms. This is consistent with the findings in Lam and Tam (2011). Assefa and Mollick (2014) have also found that liquidity is positively related to stock returns when South Africa is excluded from a sample of African markets, making liquidity priced in less liquid markets. This seems to be the overriding theme regarding liquidity in the African market and, as identified in the study of the emerging African markets, this relates to the composition of the players in the sector, with large firms dominating the small ones. The importance of liquidity is quite obvious within this index, given the problems of thin trading discussed in the literature. Kenny and Moss (1998) support this view and highlight that the small size, illiquidity and often unstable economic and political environments of African markets make them extremely volatile. Chapter 8 provides a comparative discussion of liquidity across the indices within this study.

When the contagion dummy is included within the model, I find the dummy significant. The significance of the contagion dummy identifies the importance of adjusting for time variation within the emerging African market excluding South Africa. As also seen in the South African market, the alpha term becomes positive with the inclusion of the contagion dummy; this indicates a potential for the index to outperform in stable periods.

The importance of accounting for time variation has also been identified in Oran and Soytas (2008). The contagion and liquidity-augmented four-factor model performs best within the emerging African market, excluding South Africa, with an insignificant alpha term.

5.5.2 Higher-moment CAPM in the emerging African market excluding South Africa

Table 5.11 also shows the result of the liquidity and higher-moment augmented four-factor model. One important outcome relates to the significance of the alpha term in the model, indicating the poor performance when compared to the models without the higher moments. This is similar to the findings within the South African market. The insignificance of the skewness factor and the significance of the kurtosis variable are consistent with the findings in Friend and Westfield (1980) and Hung (2008), who find that investors do not pay a premium for positive skewness of portfolio returns but that kurtosis provides some explanation of expected returns. Kim and White (2004) also found that there is no negative skewness and quite mild kurtosis.

With the significant alpha term, the conclusion that higher-moment augmented models perform better cannot be made, as also identified above. A comparative discussion of the importance of higher moments across the African market indices will be made in Chapter 6.

5.6 Empirical findings in the Frontier African market

As in the South African market, the emerging African market and the emerging African market excluding South Africa, the objective of this section is to investigate the role of the different risk factors in explaining asset pricing within the frontier African market index. The empirical results are shown in Table 5.12.

Table 5.12[157] Model performance for the frontier African market[158]

Coeff.	CAPM[159]	3-factor model[160]	4-factor model[161]	4-factor model + liquidity[162]	4-factor model + liquidity and contagion[163]	4-factor model + liquidity, contagion and higher moments[164]
α_i	0.00219295** (0.000946424)	0.00195859** (0.000933748)	0.00171708* (0.000902973)	0.00160413** (0.000862938)	0.00323144*** (0.000819579)	−0.0329551 (0.131935)
β_{iM}	0.198098*** (0.0624902)	0.209767*** (0.0623929)	0.205892*** (0.0645382)	0.217368*** (0.0614017)	0.183974*** (0.0560353)	0.188206*** (0.0567163)
β_{is}		0.0337210 (0.0207665)	0.0382279* (0.0201338)	0.0418047** (0.0207288)	0.0444451** (0.0196571)	0.0440862** (0.0186608)
β_{ih}		0.0234962 (0.0266539)	0.0450782* (0.0265515)	0.0483362** (0.0259348)	0.0445542* (0.0252050)	0.0481174* (0.025701)
β_{im}			0.0456719** (0.0193136)	0.0418725*** (0.0189410)	0.0408926** (0.0181898)	0.0406959** (0.017666)
β_{ip}				−0.0374348 (0.0317782)	−0.0419267 (0.0300360)	−0.0399902 (0.0304431)
S_i						0.00406455** (0.00187213)
K_i						0.0321275 (0.131951)
Dummy_FC_AS					−0.00679529*** (0.00245419)	−0.00806524*** (0.00285705)
R^2 Adj R^2	0.025525 0.023824	0.036249 0.031185	0.057874 0.051262	0.065063 0.056847	0.088497 0.078868	0.095577 0.082793

[157] HAC standard errors. Data source – Reuters Eikon.

[158] T = 575. *, ** and *** indicate statistical significance of the coefficient at the 10%, 5% and 1% levels.

[159] $R_i - R_f = \alpha_i + \beta_{iM}(R_M) - R_f) + \varepsilon_{it}$

[160] [160] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \varepsilon_{it}$

[161] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \varepsilon_{it}$

[162] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \varepsilon_{it}$

[163] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \delta_{iD}FCAS + \varepsilon_{it}$

[164] $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \beta_{ie}S_i + \beta_{ik}K_i + \delta_{iD}FCAS + \varepsilon_{it}$

5.6.1 Performance of the CAPM against the three-factor and four-factor models in the frontier African market

Table 5.11 reports the results of the estimation for the standard CAPM, the three-factor and the four-factor models, representing three alternative risk specifications. The Jensen alpha term, α_i, is positive and statistically significant for all three models, indicating a poor fit with established theoretical CAPM assumptions. This is contrary to findings in Hearn and Piesse (2009), which identified that Jensen alpha terms are not statistically significant within the African market.

An interesting finding from this study relates to the goodness of fit (R^2) of the models. These are quite low when compared to most findings in the literature, with the adjusted R^2 for the one-, three- and four-factor models being 2.38%, 3.12% and 5.13%, respectively. Although this suggests an improved goodness of fit for the Carhart four-factor model, these values are quite low when compared to the R^2 values for the emerging African market and the South African market. There are some recent studies that also find low R^2 values in the African market such as Tunyi and Ntim (2016).

The estimate of beta for the Sharpe-Lintner CAPM model was positive and significant at the 1% level, indicating a good fit with the predictions in Sharpe (1964) and Lintner (1965). Beta is also positive and significant within the Fama-French three-factor model; however, the size factor is insignificant. This corresponds to findings in van Dijk (2011), who identifies that the strength of the size effect can depends on market characteristics such as the type of investor, trading mechanism and market efficiency in general. Horowitz et al. (2000a,b) and Amihud (2002) have identified that the size effect disappeared after the early 1980s. The value factor is also insignificant in the frontier African market. Empirical findings in Loughran (1997) indicate that there is no consistent relationship between book-to-market value and returns, with Kothari et al. (1995) arguing that the value premium is due to survivorship bias.

The variables within the Carhart four-factor model are all significant at conventional levels. This also includes the alpha term, which indicates that the model performs poorly when compared to theoretical expectations. Beta, size, value and momentum are all positive, indicating that the frontier African market conforms to theoretical expectation within the Carhart four-factor model; see Carhart (1997). This indicates that the momentum factor is jointly important with the size and value factors within the frontier market.

5.6.2 Liquidity-augmented four-factor model in the frontier African market

In Table 5.11, we also report the results of the liquidity-augmented models. The liquidity factors are all negative and insignificant, indicating that liquidity is not priced in the frontier African market. This contradicts the findings in Lee (2011), Amihud and Mendelson (1986) and Pástor and Stambaugh (2003), who believe that liquidity should be a priced state variable and that the liquidity premium should be positive. However, as stated in Hearn (2011), the effect of liquidity depends on the structure of the surveyed stock market, while Lischewski and Voronkova (2012) find conflicting results on the relevance of liquidity in asset pricing. The importance of liquidity within the frontier market compared to the other markets in our sample will be discussed in greater detail in Chapter 6.

5.6.3 Effect of contagion on the liquidity-augmented four-factor model in the frontier African market

When the contagion dummy variable (for the financial crisis and Arab Spring) is included in the liquidity-augmented four-factor model, the results remain the same, while the dummy variables are negative and significant all at the 1% level. This indicates the importance of variation in CAPM estimates, as the financial crisis and Arab Spring have affected the returns-generating process within the frontier African market.

The instability in beta has been well documented, with Lettau and Ludvigson (2001), Lustig and Van Nieuwerberburgh (2005) and Santos and Veronesi (2006) examining the beta of small, high B/M stock over the business cycle and finding that their beta varies with the business cycle. They also found that these variations can explain the positive unconditional alpha found for these stocks. However, as seen in this market, the inclusion of the contagion dummy has not improved the alpha term. This contradiction when compared to the findings in the South African and emerging African markets will be discussed in Chapter 6.

5.6.4 Higher-moment augmented model in the frontier African market

The liquidity- and higher-order moment augmented four-factor model, with a contagion-effect dummy, seems to be the "best" model within the frontier African market. This is because the results show an insignificant Jensen alpha term, indicating a good fit theoretical CAPM assumption.

The adjusted R^2 for this model indicates its better performance when compared with the other models in the frontier African market, with an adjusted R^2 of 8.28%. We find the skewness measure to be significant along with beta, size, value, momentum and the contagion dummy variable. The performance of this model and the importance of the skewness factor are supported by Harvey and Siddique (2000). They demonstrate the importance of skewness in a skewness-augmented three-factor model. They also concluded that, in general, models incorporating coskewness are helpful in explaining the cross-sectional variation of equity returns.

The significance of the contagion dummy and the findings in Ariff and Johnson (1990) support its importance of accounting for time variation in estimates of the CAPM. Harvey (1994) suggests that risk exposure significantly changes through time for a number of emerging market countries as their industrial structure develops. This is particularly the case for countries that are less integrated with world capital markets. Bos and Fetherston (1992) have also investigated beta instability in the Korean and Singaporean markets, respectively.

5.7 Chapter conclusion

This chapter investigates the risk-return characteristics of the South African basic materials index, the emerging African market's basic materials index, the basic materials index of the emerging African market excluding South Africa and the frontier African market using weekly return data from January 2004 to December 2014. It examined the Sharpe-Lintner CAPM, the Fama-French three-factor model, the Carhart four-factor model and includes the liquidity factor and higher-order moments in a step-wise regression model. It also examined the role of contagion in explaining returns within the liquidity-augmented four-factor model. The objective of this approach was to investigate the role of the different risk factors on asset pricing within the South African basic material index.

The Jensen alpha terms, α_i, are not statistically different from zero for the three and four-factor models, indicating a good fit with established theoretical CAPM assumptions within the South African market. However, the Sharpe-Linter CAPM had significant alpha term, demonstrating its poor performance in explaining realised returns. Within the emerging African market, the Jensen alpha terms, α_i, were significant for the one-, three- and four-factor models. The alpha term remained significant even after the liquidity factor was added to the four-factor model. A marked difference was highlighted when the dummy variable for contagion was introduced into the models. The result indicate that the exogenous shock had a profound effect on the dataset, showing that the dummy variable was negative and significant at the 1% level, with the alpha term being insignificant. This highlights the importance of accounting for time variations in estimates of the CAPM within the emerging African market, thereby refuting the commonly made assumption that beta remains constant over time.

For the emerging African market excluding South Africa, the alpha terms are insignificant for all models except when higher moments are included, indicating that the models perform better within this market when compared with the emerging African market. For the frontier African market, the findings indicate that the Jensen alpha term, α_i, is positive and statistically significant for all models except the liquidity- and higher-moments adjusted four-factor model when contagion is accounted for, indicating a poor fit for other models with established theoretical CAPM assumptions.

Within the South African market, the study finds that the explanatory power of the model increases with additional size, book-to-market value and momentum. This demonstrates the improved explanatory power of the Fama-French and Carhart models over the Sharpe-Lintner standard CAPM within the South African market.

As expected, beta was found to be positive and statistically significant for the standard, three-factor and four-factor CAPMs. But unlike most studies that identify a size premium, size was found to be negative and statistically significant, indicating that large firms outperform small firms in the South African market. This difference is explained by industry-specific factors and also by specific characteristics of the African market as explained in Hearn and Piesse (2009). The book-to-market value and momentum factors were insignificant.

Due to the importance of liquidity, as established in recent literature, I adjusted the four-factor model by including a liquidity variable. I found that the market beta and size were significant, along with the liquidity factor, but the book-to-market value and momentum factors continued to be insignificant. This corresponds to the findings of Bundoo (2008), who highlights that there is a lack of empirical evidence as to whether the value premium is present in emerging equity markets generally, and particularly in the emerging African stock markets. Hence I can conclude that accounting for beta, size and liquidity factors eliminates the relevance of the value and momentum factors in asset pricing within the South African market.

However, the liquidity factor had a negative relationship with returns. This means that investors are not compensated for holding illiquid stocks, as liquid stocks outperform illiquid stocks.

This contradictory finding may be due to tax systems, market microstructure, industry characteristics, improvements in market structures and the opening of the South African markets to foreign investors.

When the effect of contagion (the financial crisis and the Arab Spring) is accounted for within the four-factor models where the contagion dummy was found to be significant, indicating possible time variation effects, the contagion dummy did not, however, change the result of the other variables in the South African market.

Lastly, I incorporated the systematic skewness and kurtosis by examining the importance of the higher moments in explaining returns within a liquidity-adjusted four-factor model. Quite unexpectedly, the analysis uncovered that both coskewness and cokurtosis are not important in pricing stock on the South African basic materials index. One reason that could explain the result is parameter uncertainty resulting from the use of observed information in estimating unknown parameters and also due to unstable predictive relations; this has also been identified in Lewis (2006) and Paye and Timmermann (2006).

The four-factor model that accounts for liquidity and contagion was found to perform best in the South African market.

However, within the emerging African market, the liquidity-augmented four-factor model performs better when the contagion effect is controlled, as its alpha term is closest to zero. However, in terms of goodness of fit, the liquidity- and higher-moment augmented four-factor model performs better with the highest adjusted $R^2$of 39.82%. However, the alpha term is significant, hence with an R^2 of 39.35% and with a constant term closest to zero, the liquidity-augmented four-factor model that controls for contagion performs better within the emerging African market.

The chapter also finds beta, size and kurtosis to be positive and significant within the emerging African market, while book-to-market value, momentum, liquidity and skewness were insignificant. The dummy variable for contagion was found to be significant within the liquidity-augmented four-factor model that controls for contagion.

For the emerging African market excluding South Africa, the alpha terms are insignificant for all models except when higher moments are included, indicating that the models perform better within this market when compared with the emerging African market. The liquidity-augmented four-factor model performs best within the emerging African market excluding South Africa, with a high adjusted R^2 of 62.03% and an insignificant alpha term when the contagion effect is controlled for. All the variables are significant except the skewness measure. However, one interesting finding is that the direction for some of the variables is different when compared with the findings in the emerging African market.

The size factor is positive and significant in the emerging African market, indicating that small firms perform better than big firms, but the size effect is negative in the emerging African market excluding South Africa, indicating that big firms perform better. The value factor in negative but insignificant in the emerging African market, but positive and significant in the emerging African market excluding South Africa. The momentum factor is positive and significant in both markets, while the liquidity factor is not significant in the emerging African market but positive in the emerging African market excluding South Africa. The kurtosis factor is both positive and significant for both markets.

The results also demonstrate the importance of accounting for time variation in the African market, as the contagion dummies were significant except within the models that account for higher moments.

The models clearly performed better in the emerging African market excluding South Africa than in the emerging African market including South Africa. This is due to the interaction between the characteristics of the South African market with those of Egypt and Morocco. This results from varying levels of integration of the market with developed markets as stated in Stulz (1999). Also, the characteristics of the South African market differ from those of Egypt and Morocco in terms of levels and impact of political instability, religious background, market development, investor protection and legal system within the country.

For the frontier African market, the adjusted R^2 of the models was quite low when compared with the R^2 in the South African market and the emerging African markets. Beta was, however, significant across all models while size and value were insignificant within the three-factor model, but significant when the momentum factor was introduced using the four-factor model and for other models with the momentum factor was also significant.

I found liquidity to be unimportant within the frontier African market, when the contagion-effect variable was significant, demonstrating the impact of the financial crisis and the Arab Spring on the frontier African market index. When the liquidity- and contagion-effect four-factor model includes the effect of higher moments, I find that the alpha terms become insignificant with some increase in the R^2; hence I conclude that the higher-moment augmented models perform better within the frontier African market. However, the skewness measure is significant, while the kurtosis measure is insignificant.

Therefore, I conclude that the liquidity- and higher-moment augmented model performs best within the frontier African market when the contagion dummy variable is introduced. I find that beta, size and value to be significant except within the three-factor model. Momentum, skewness and the contagion variable were also significant.

In Chapter 6, I compare the performance of the models in the various indices and identify the implications of the results for asset pricing in the African market.

5.8 Chapter appendices

South African market

Figure A 5.1 Frequency distribution with Doornik-Hansen test for normality for the market portfolio (South Africa)

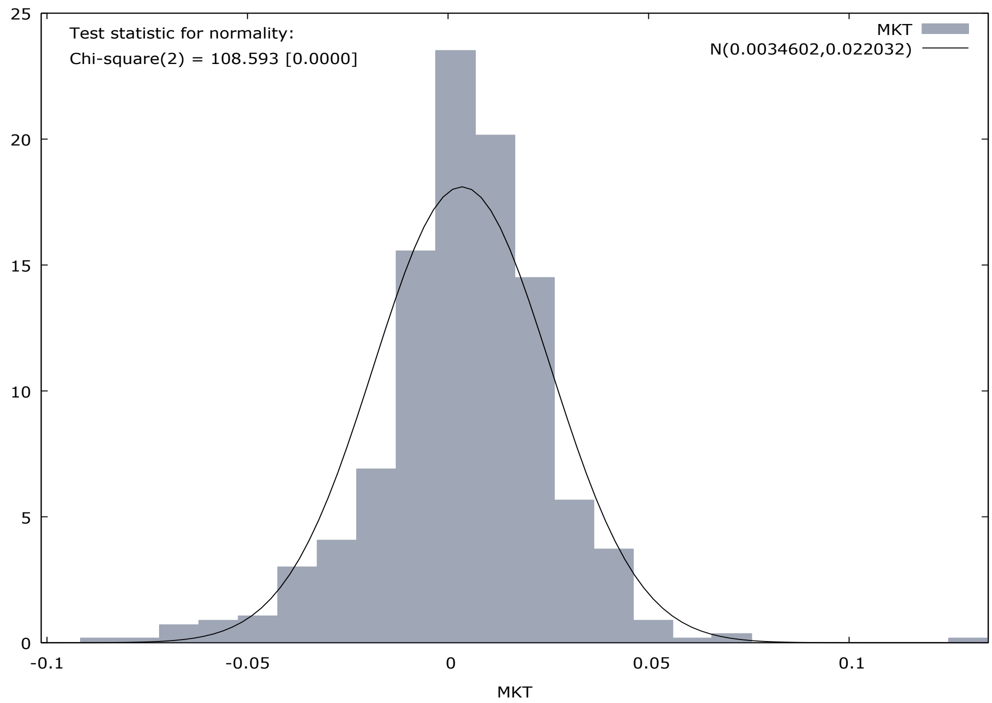


Figure A 5.2 Market portfolio correlogram (South Africa)

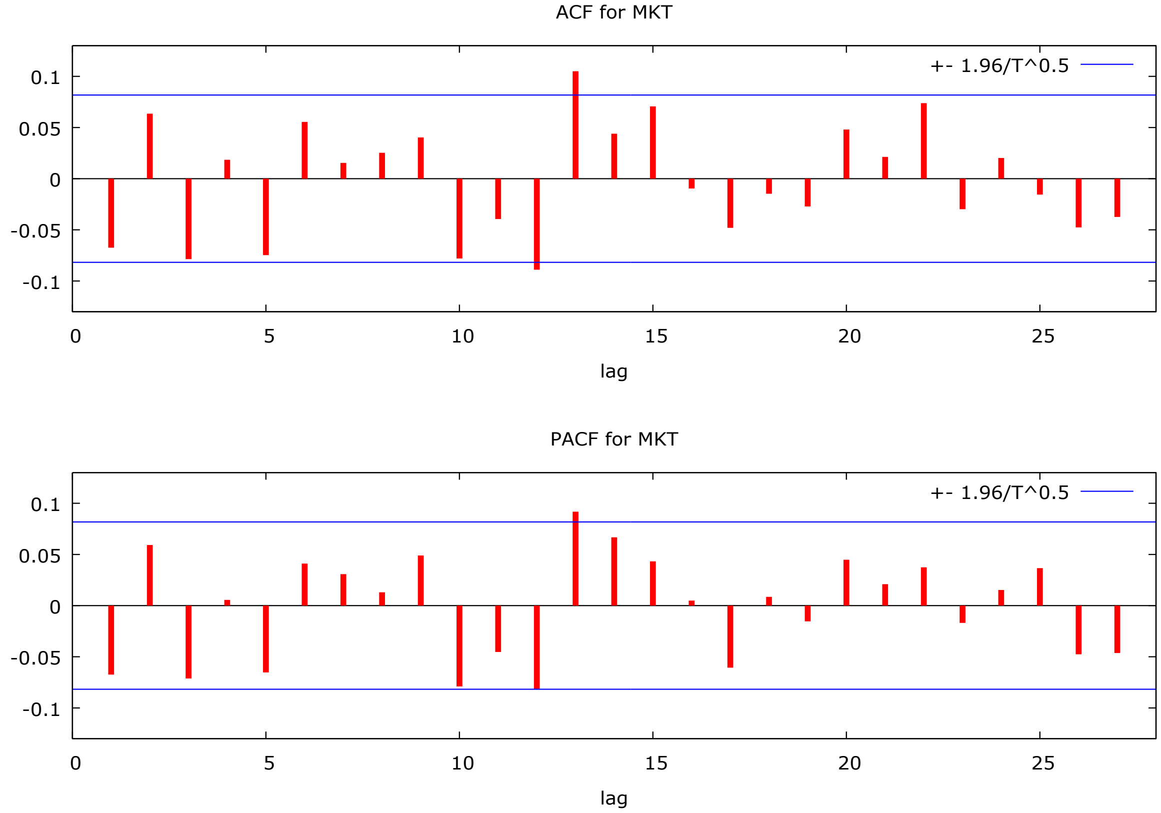


Figure A 5.3 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on size (South Africa)

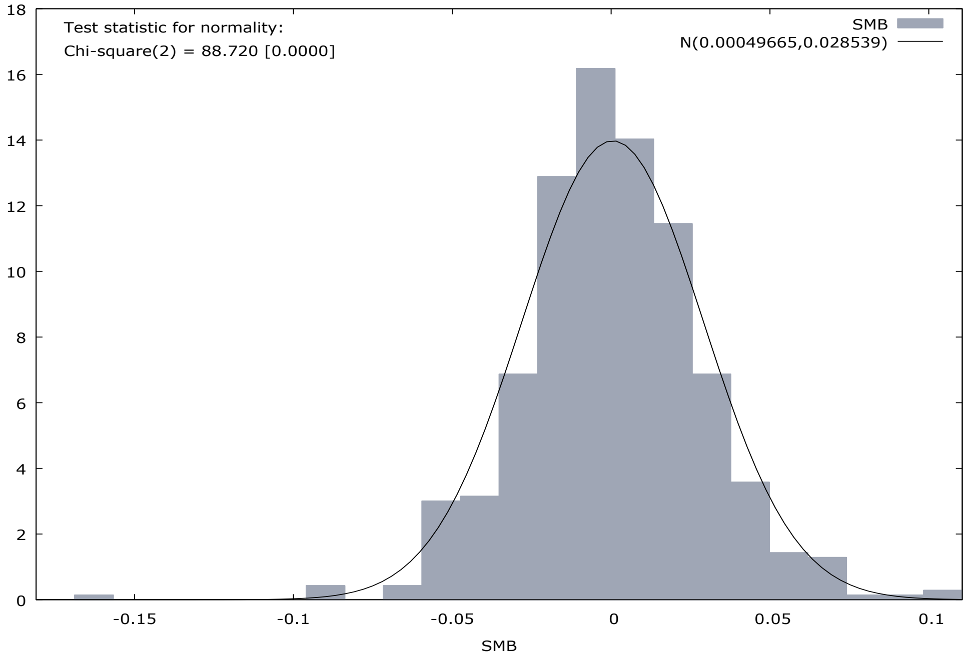
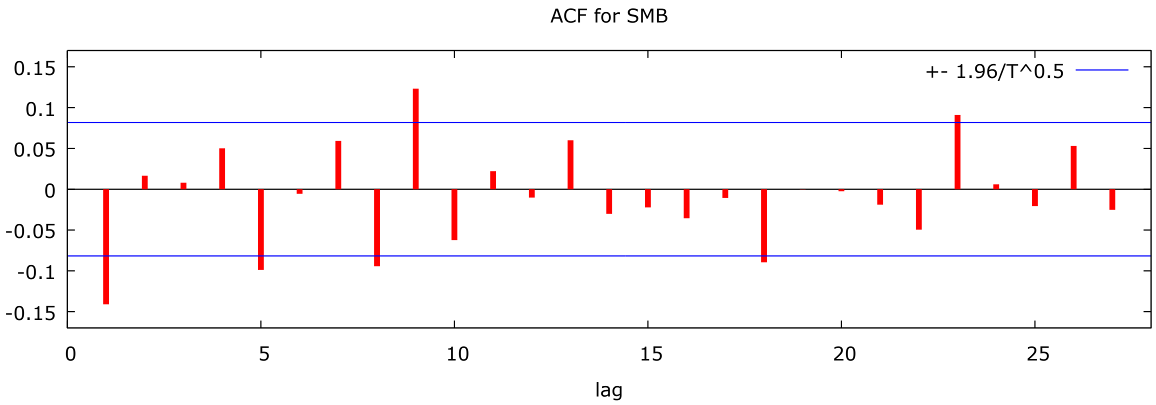


Figure A 5.4 Size portfolio correlogram (South Africa)



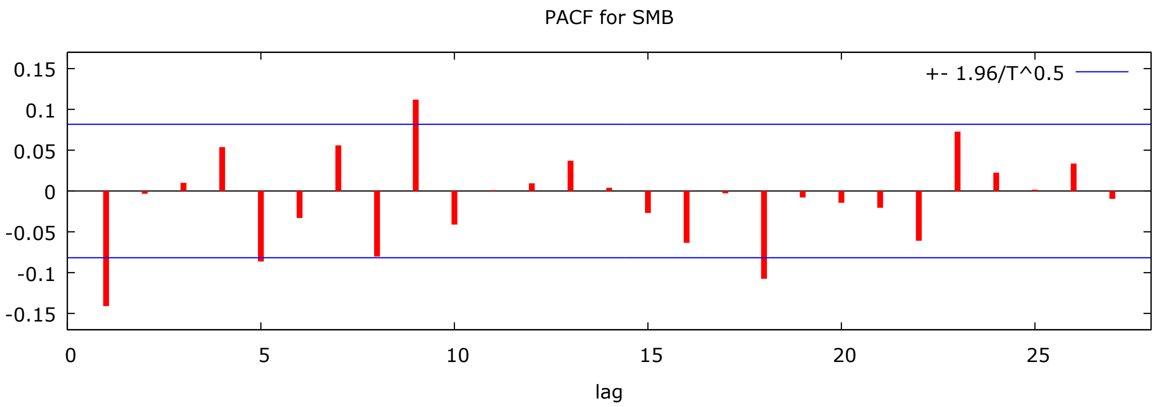


Figure A 5.5 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on value (South Africa)

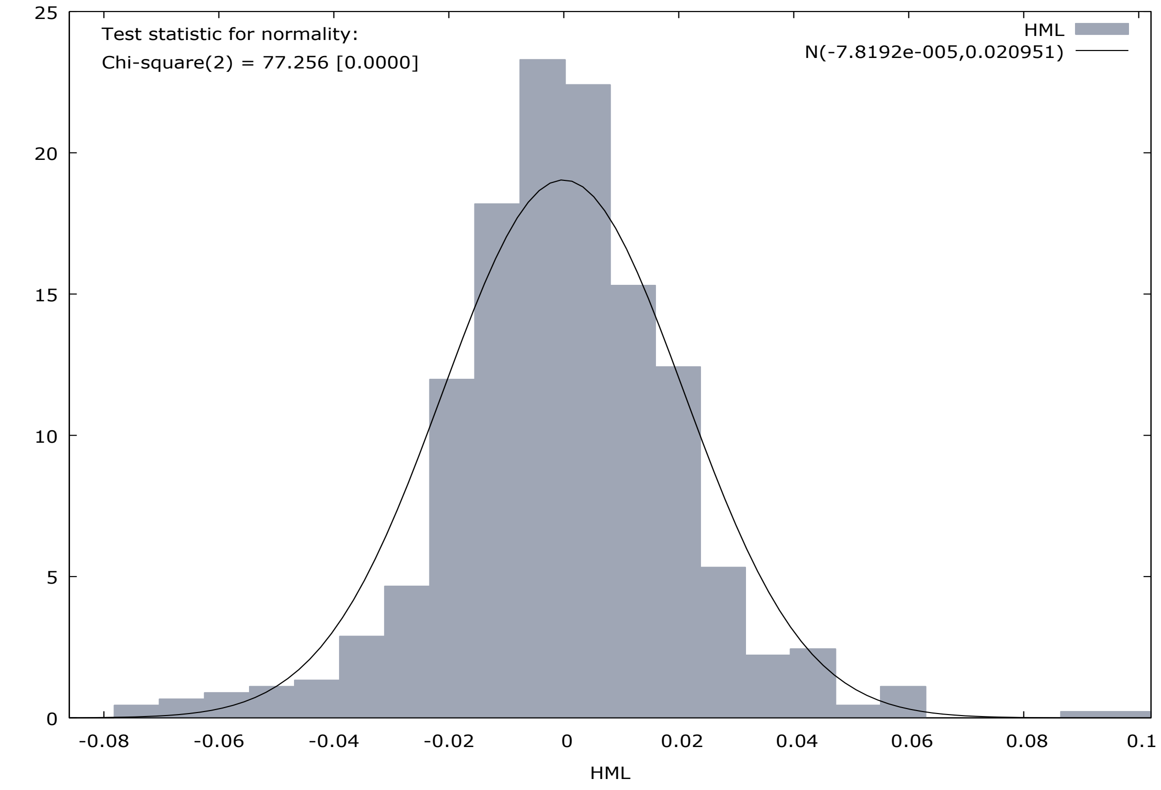


Figure A 5.6 Value portfolio correlogram (South Africa)

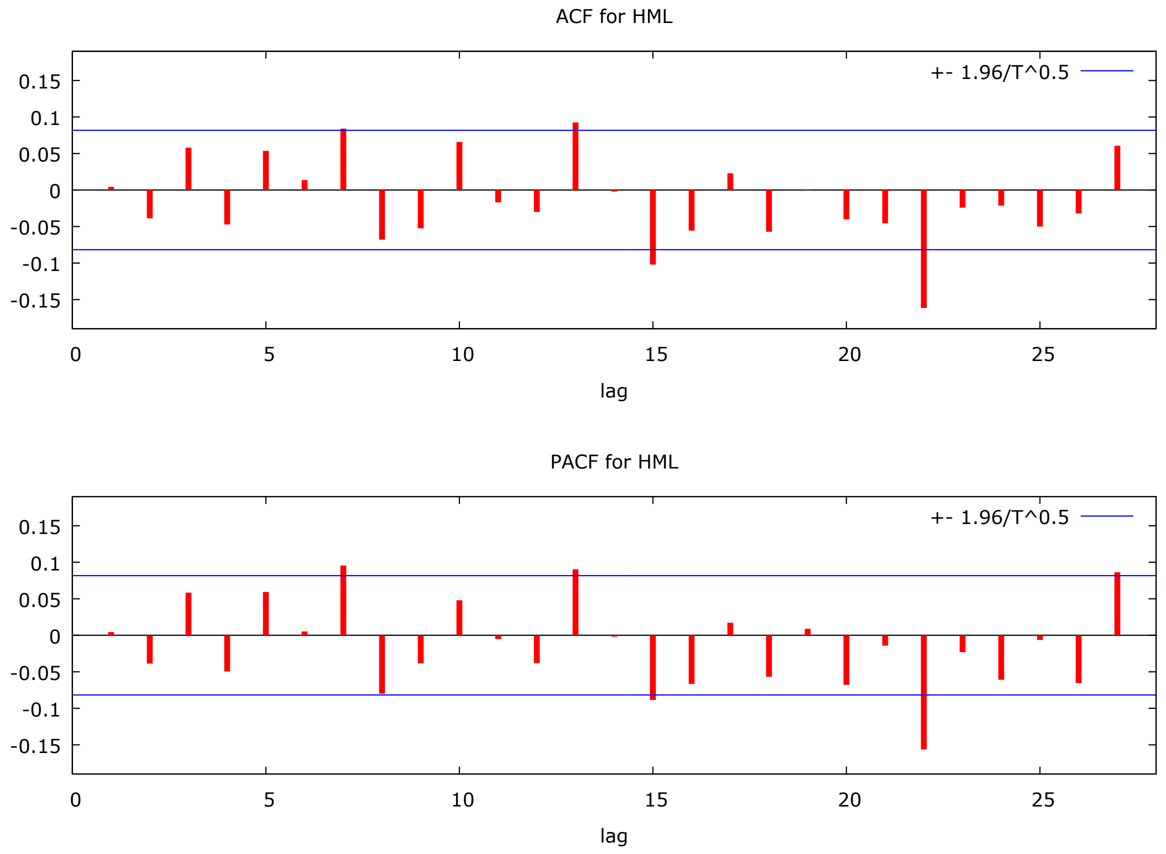


Figure A 5.7 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on the momentum factor (South Africa)

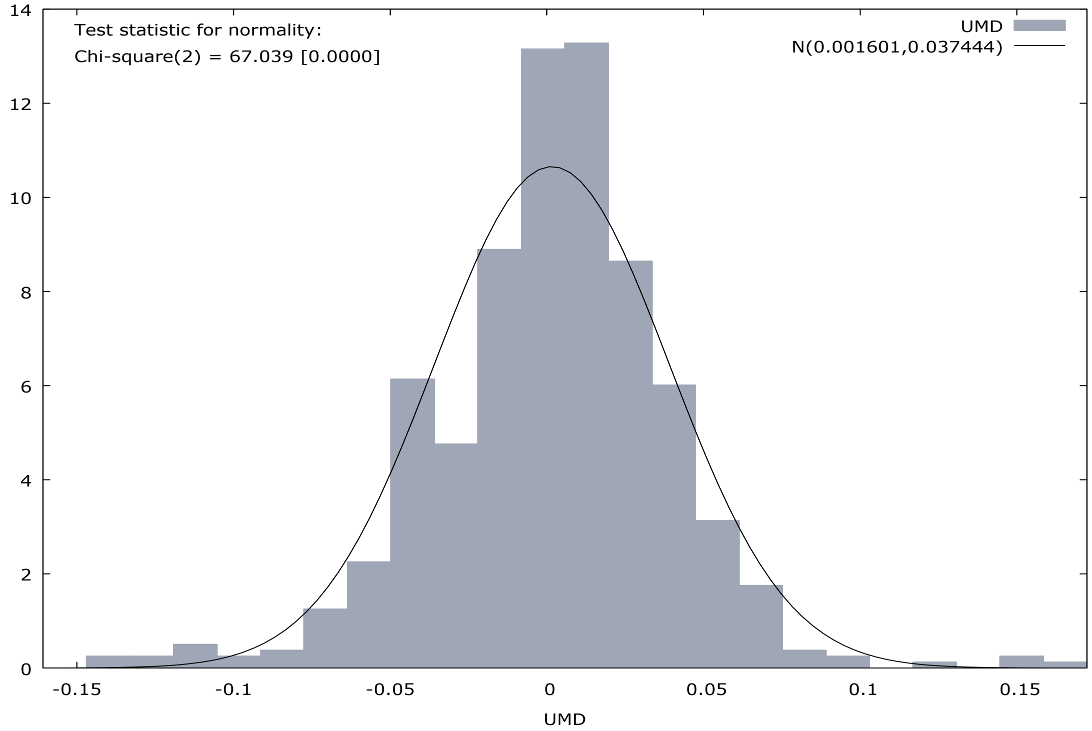
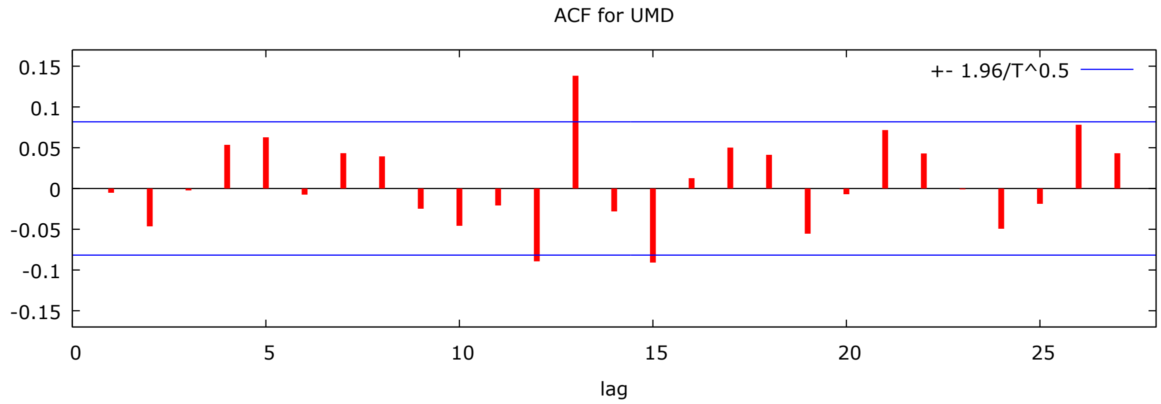


Figure A 5.8 Momentum portfolio correlogram (South Africa)



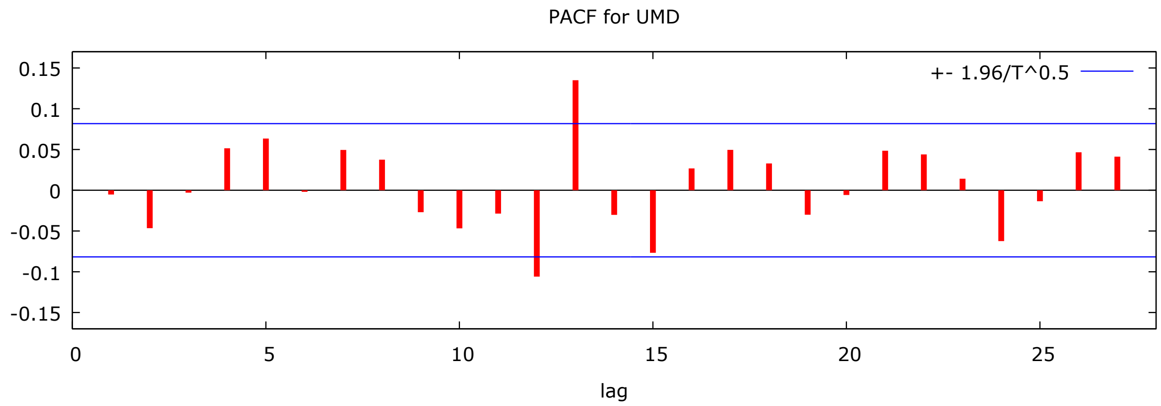


Figure A 5.9 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on the liquidity factor (South Africa)

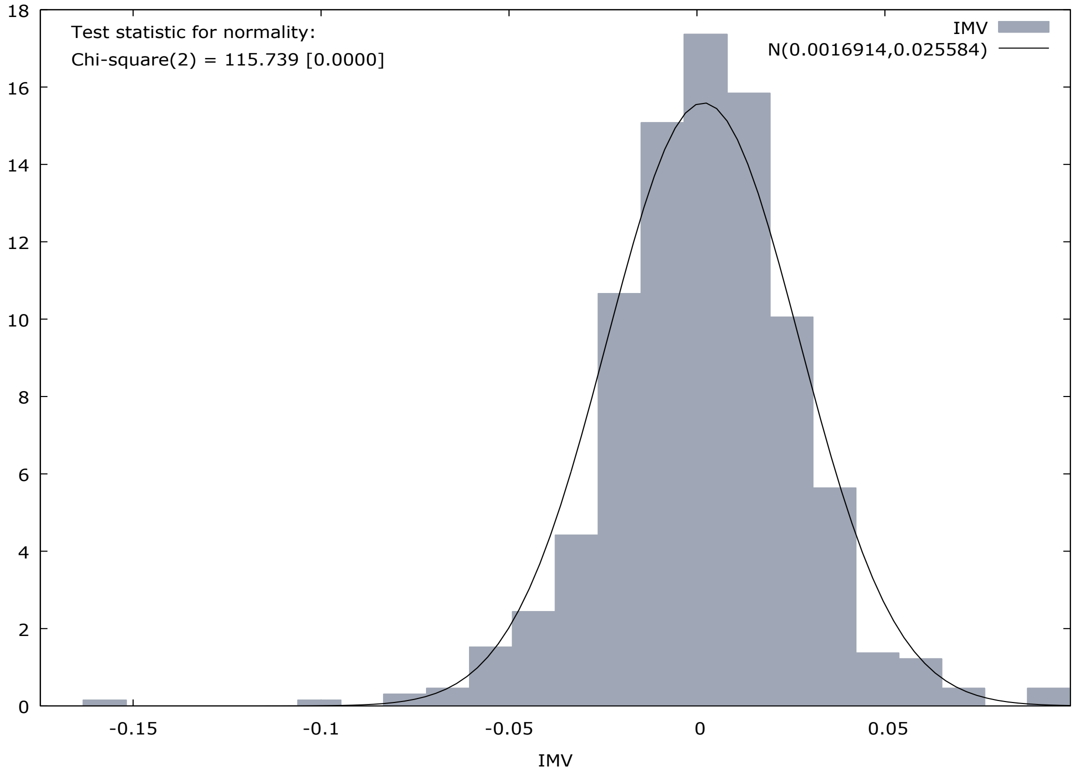


Figure A 5.10 Liquidity potfolio correlogram (South Africa)

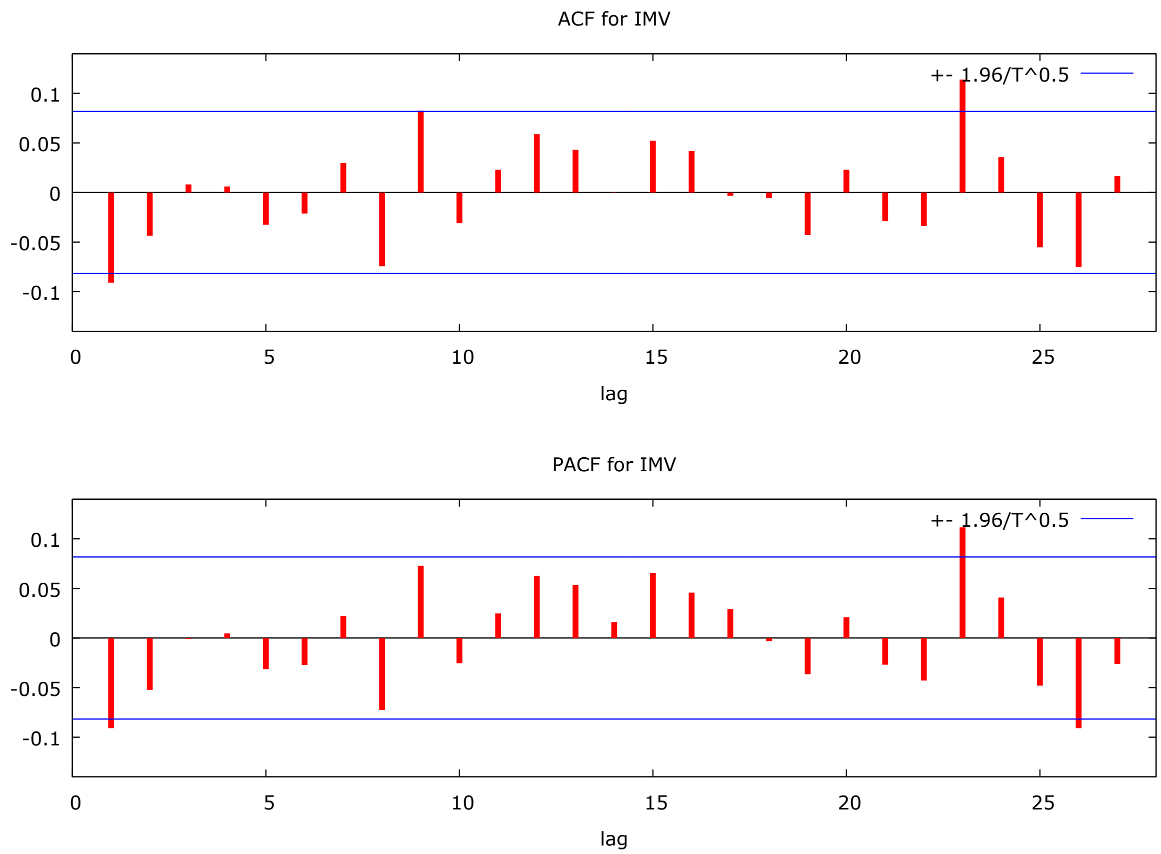


Figure A 5.11 Frequency distribution with Doornik-Hansen test for normality for the skewness (S_i) measure (South Africa)

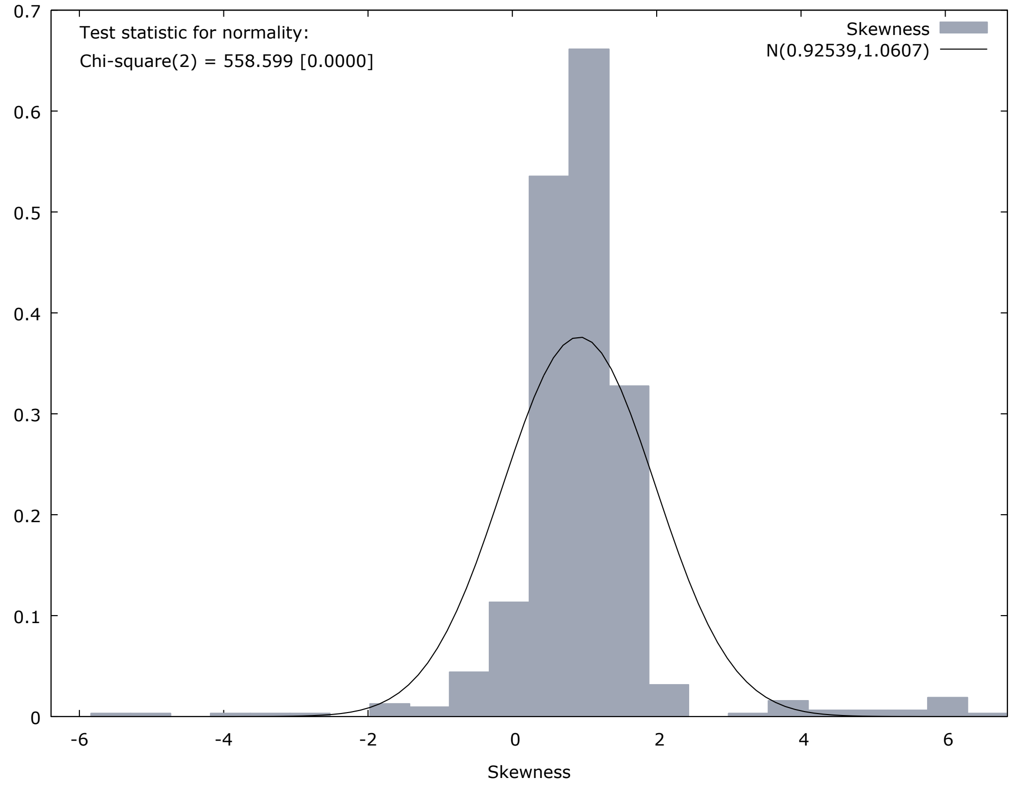


Figure A 5.12 Correlogram for the skewness (S_i) measure (South Africa)

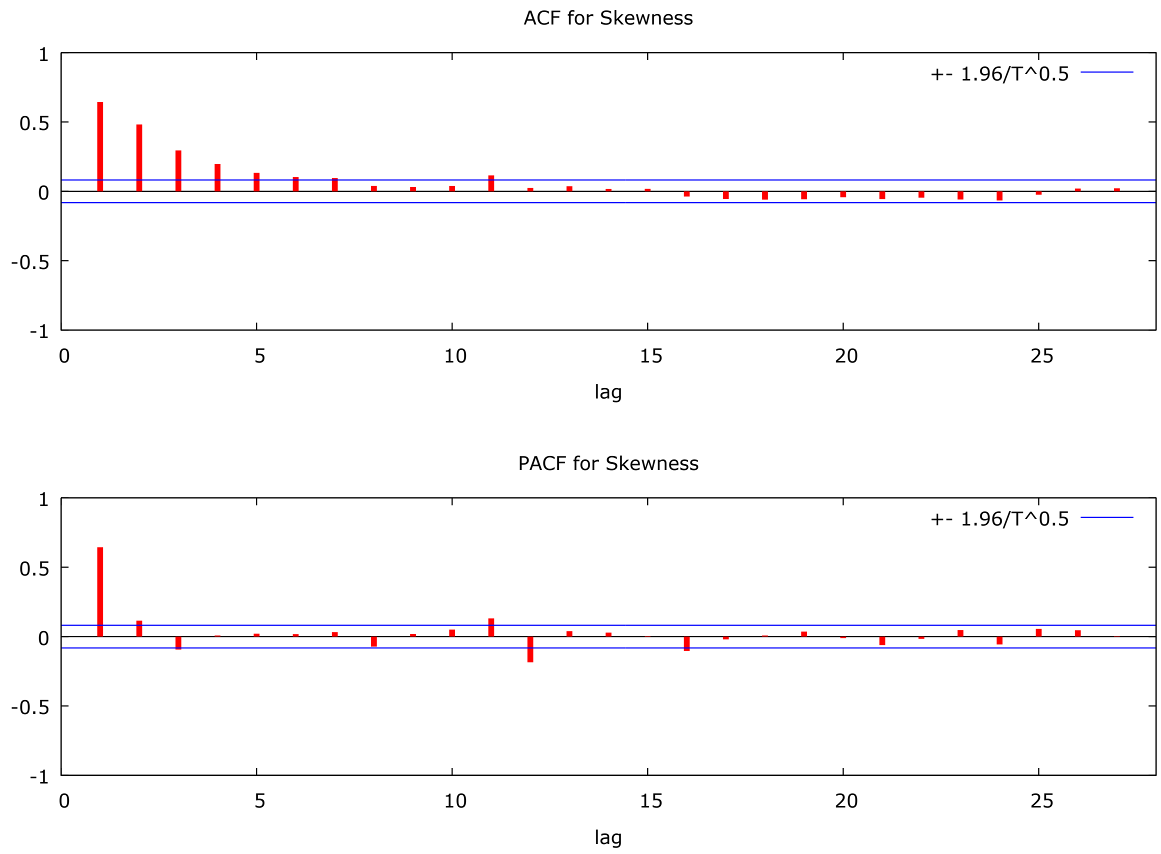


Figure A 5.13 Frequency distribution with Doornik-Hansen test for normality for the kurtosis (K_i) measure (South Africa)

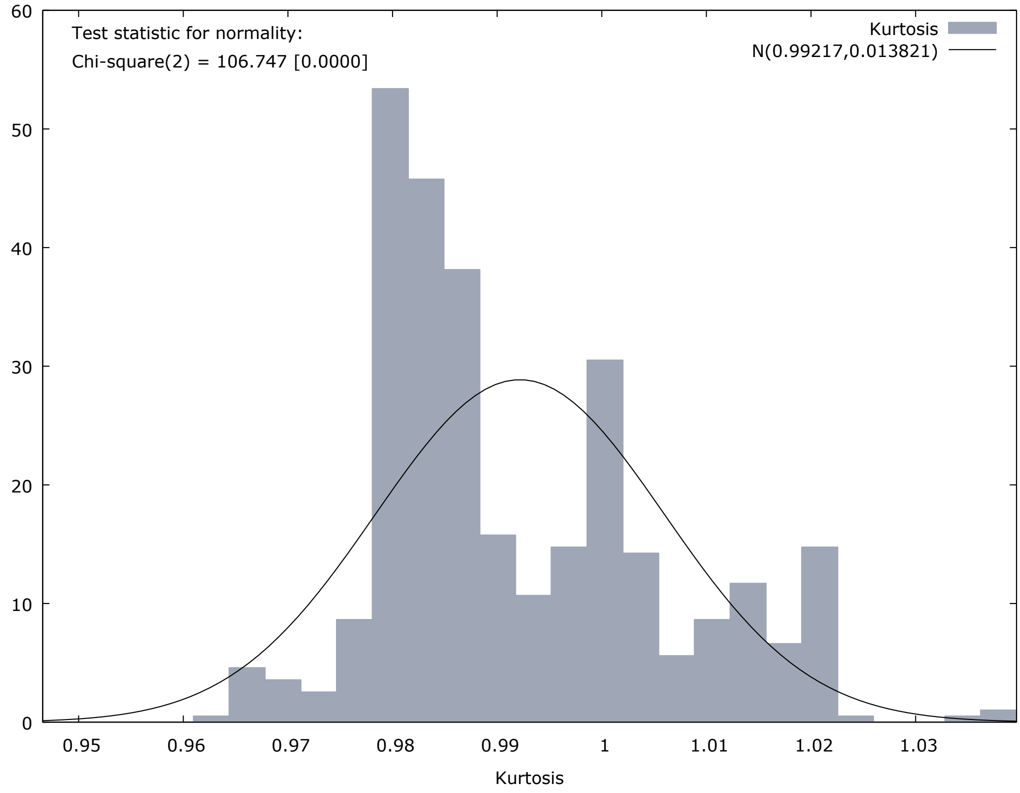
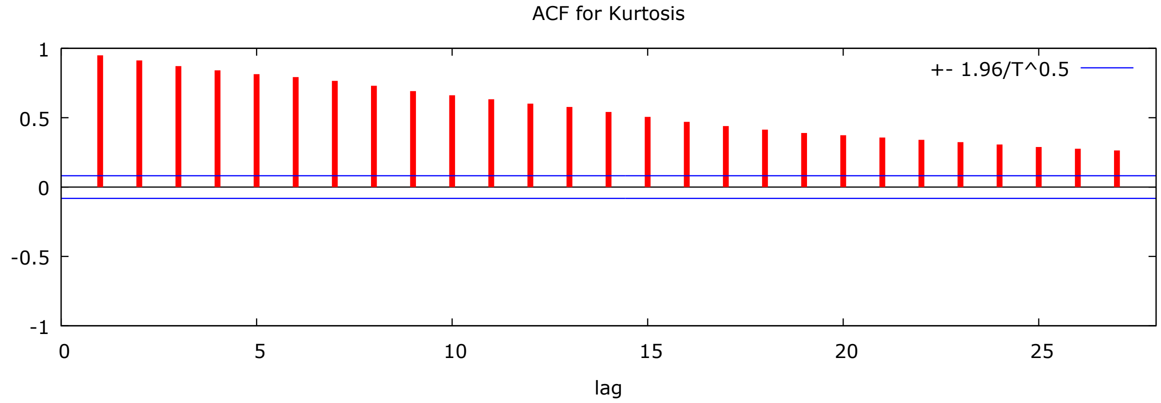
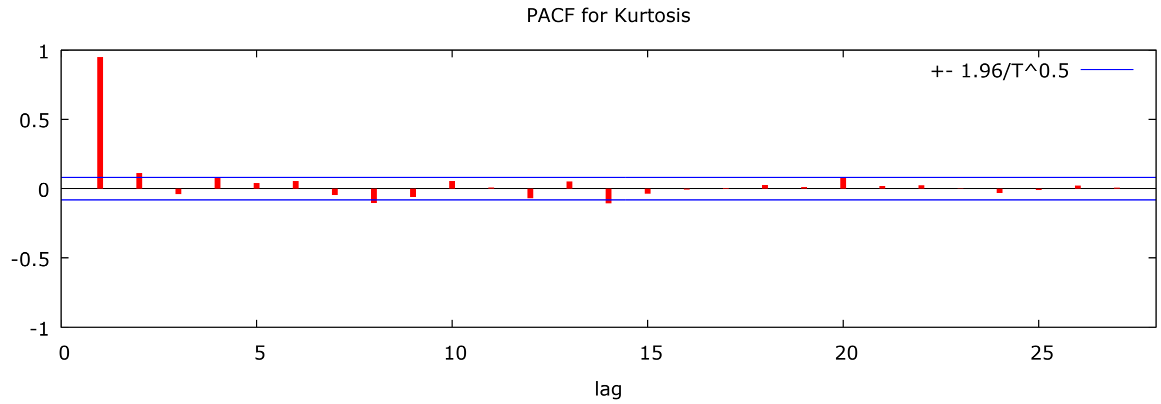


Figure A 5.14 Correlogram for the kurtosis (K_i) measure (South Africa)





Emerging African market

Figure A 5.15 Frequency distribution with Doornik-Hansen test for normality for the market portfolio (emerging African market)

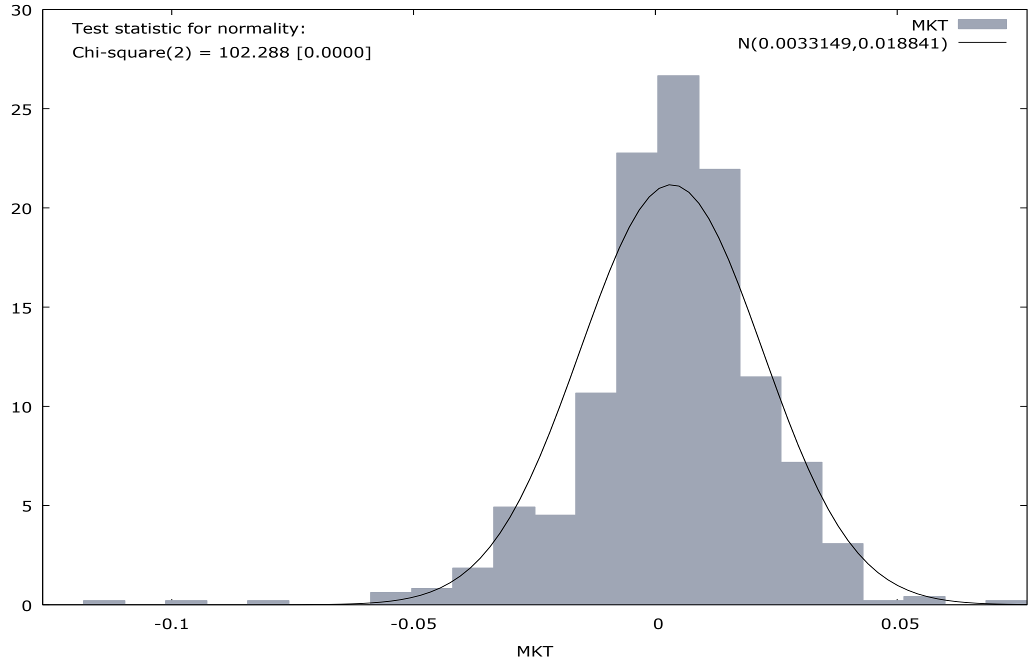


Figure A 5.16 Market portfolio correlogram (emerging African market)

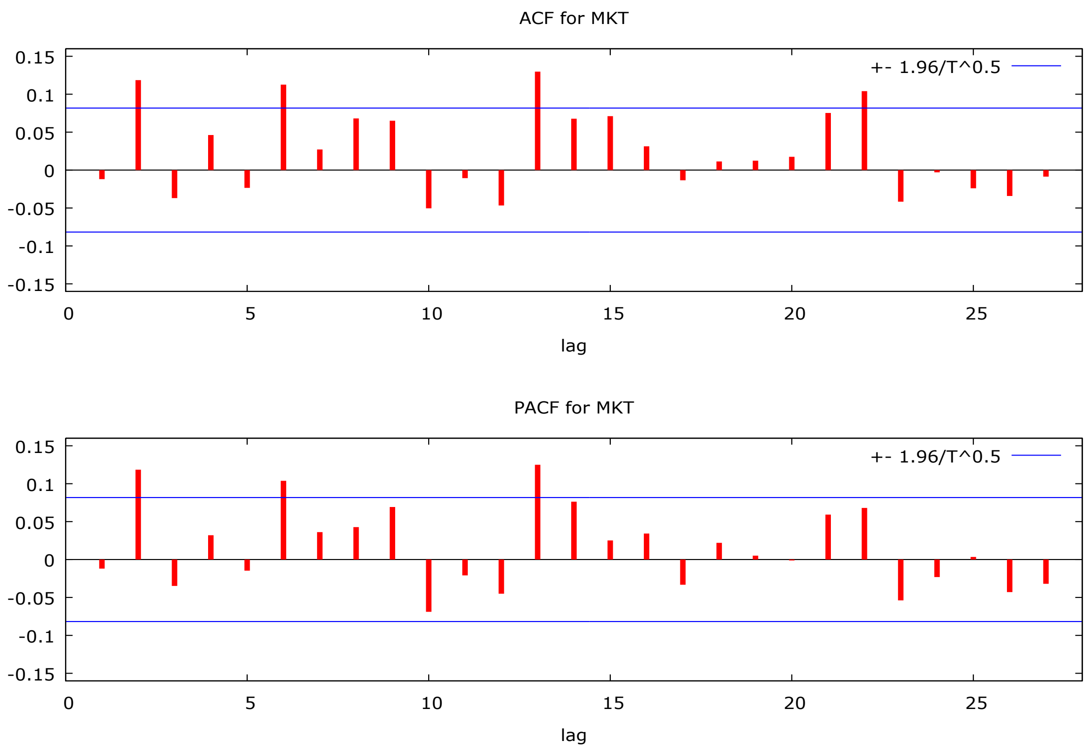


Figure A 5.17 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on size (emerging African market)

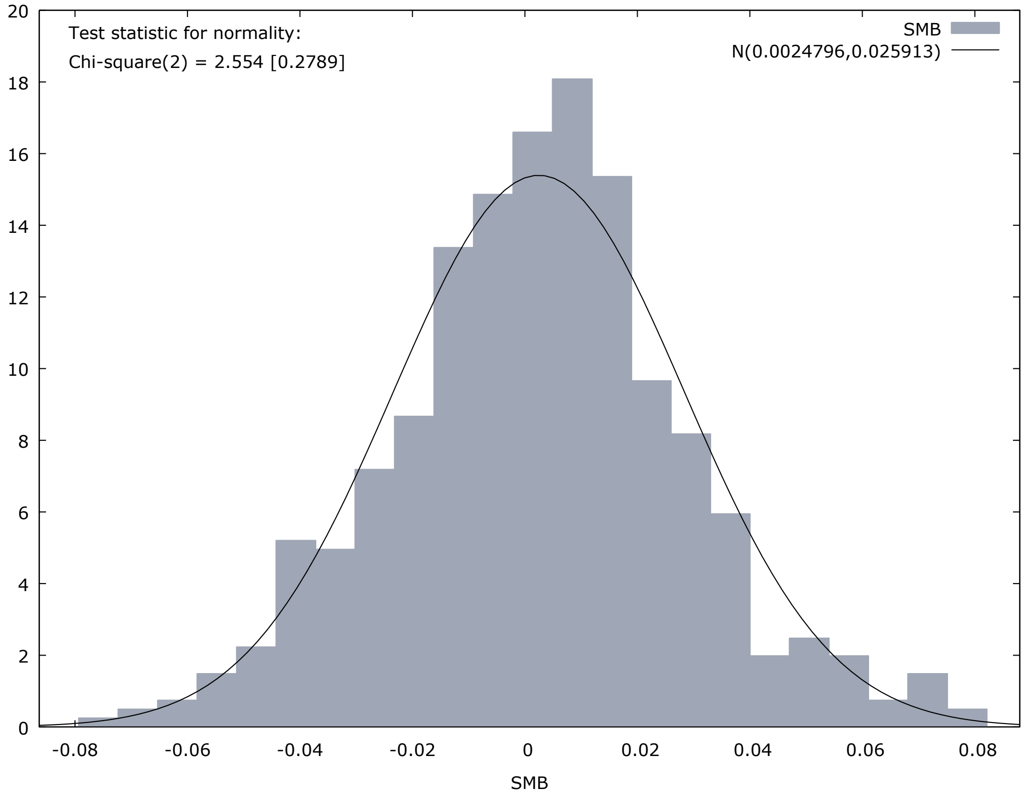


Figure A 5.18 Size portfolio correlogram (emerging African market)

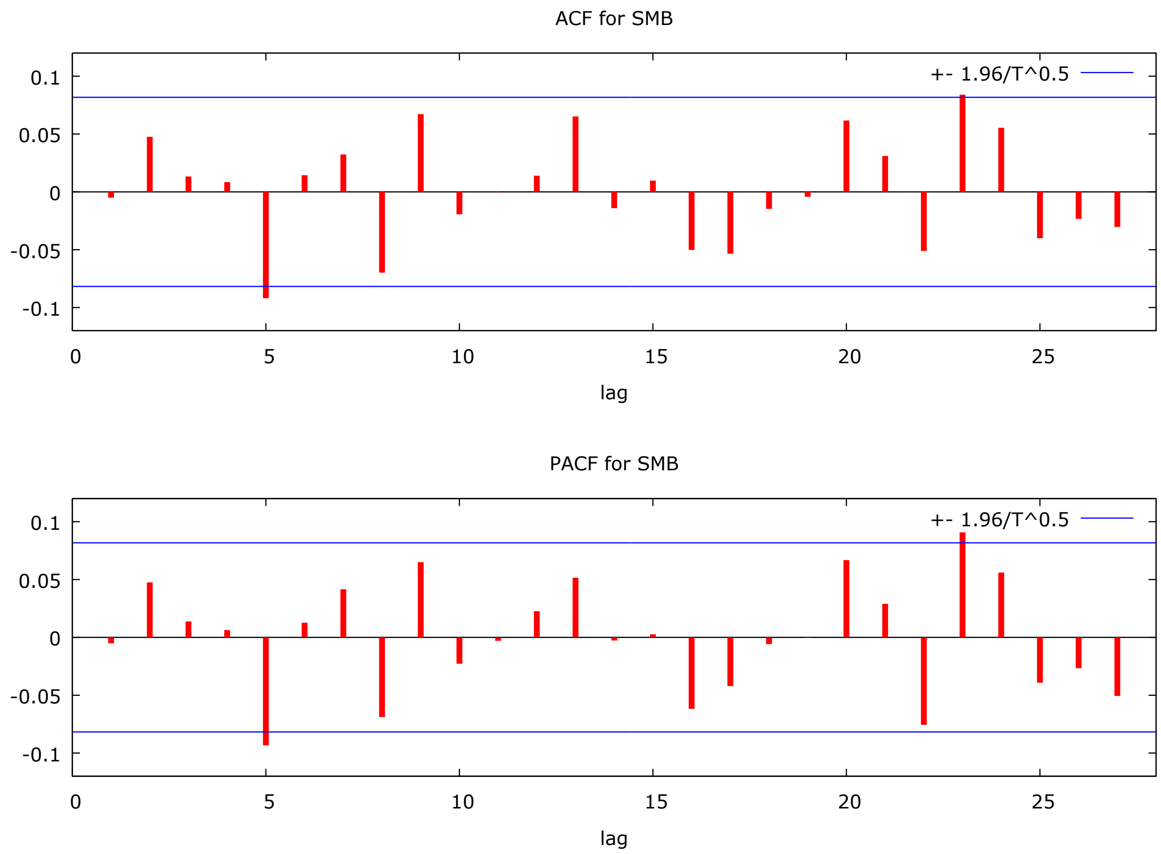


Figure A 5.19 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on value (emerging African market)

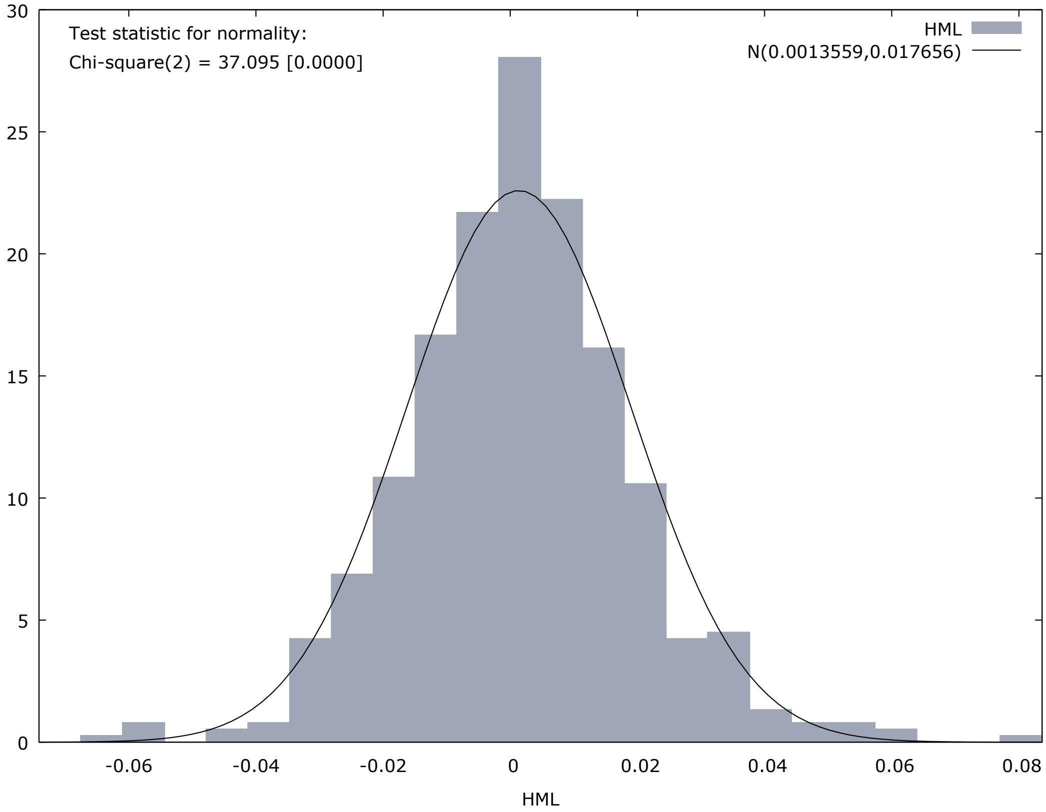
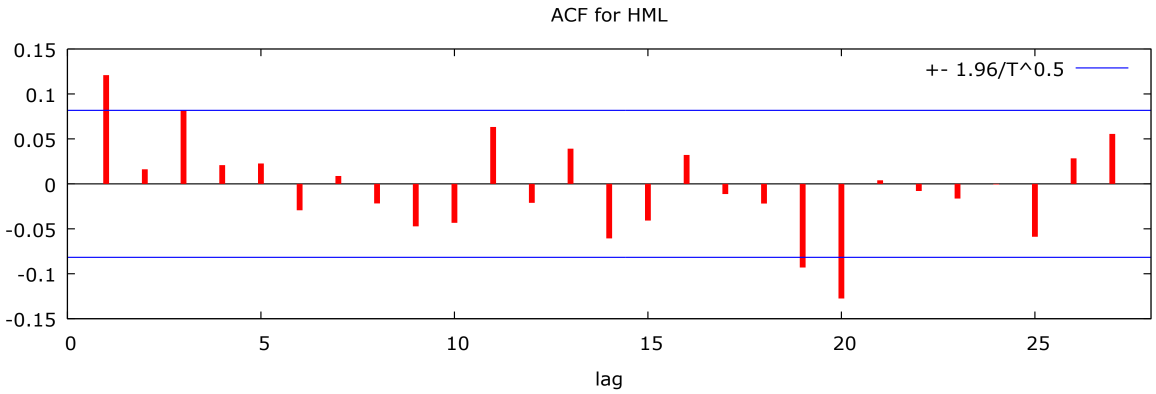


Figure A 5.20 Value portfolio correlogram (emerging African market)



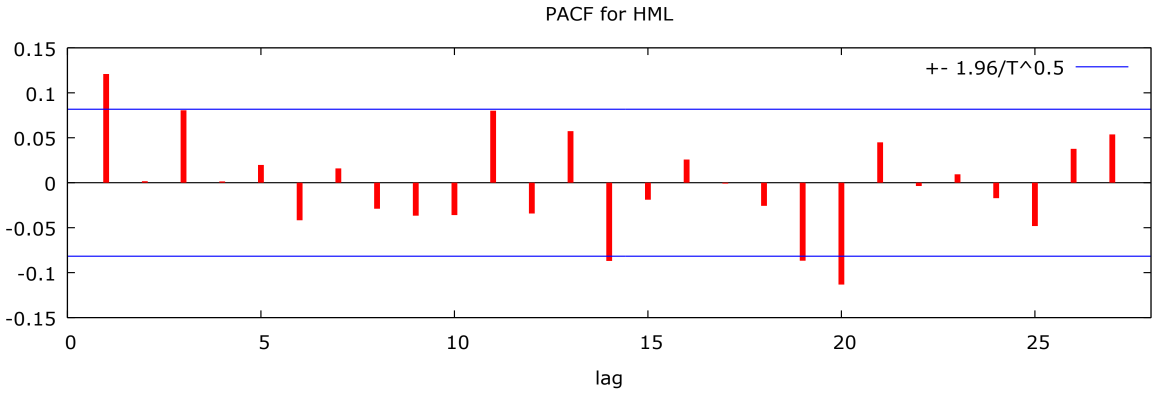


Figure A 5.21 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on the momentum factor (emerging African market)

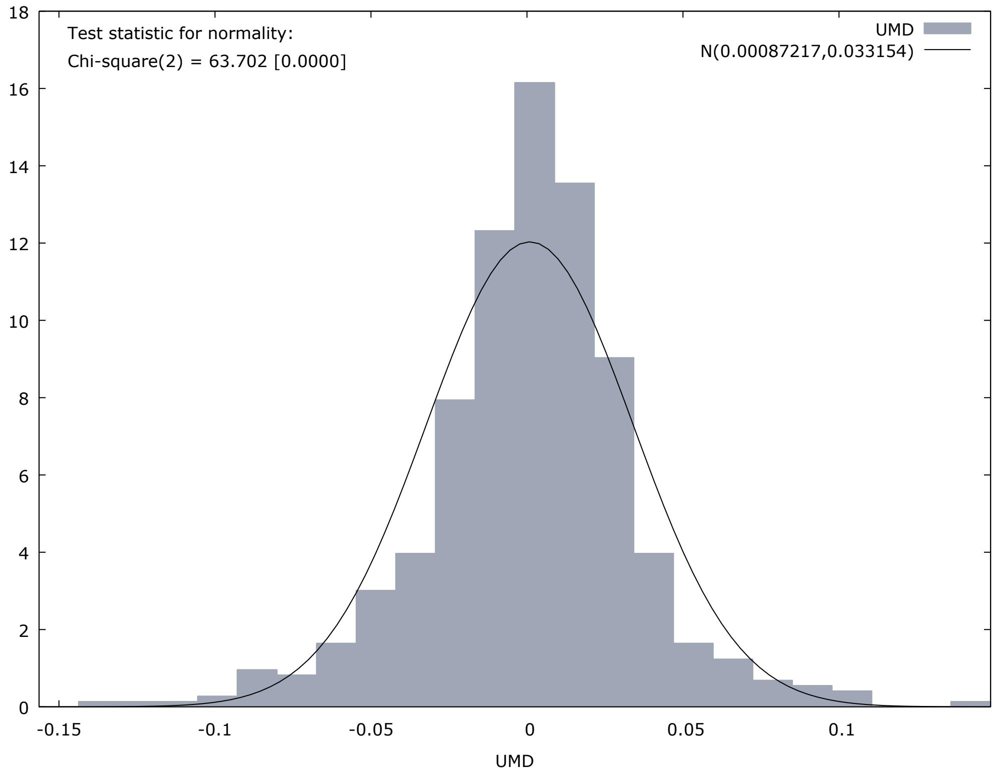
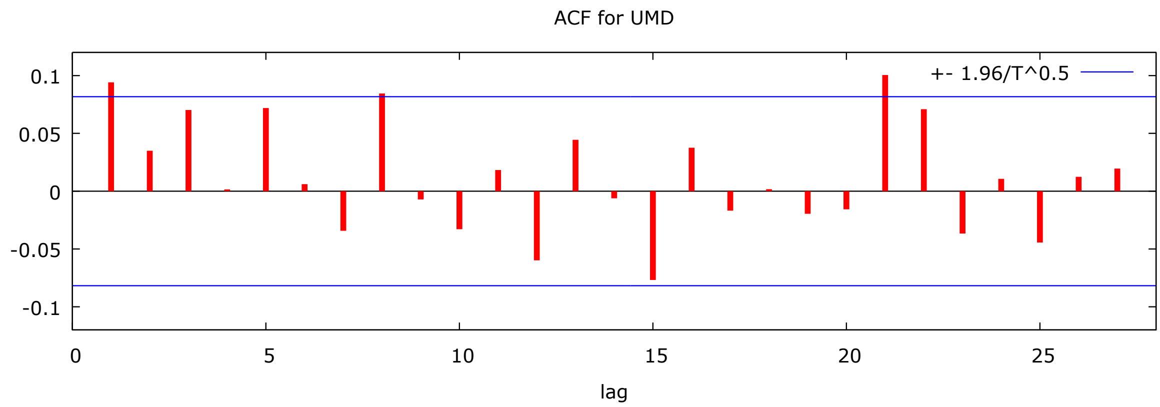


Figure A 5.22 Momentum factor correlogram (emerging African market)



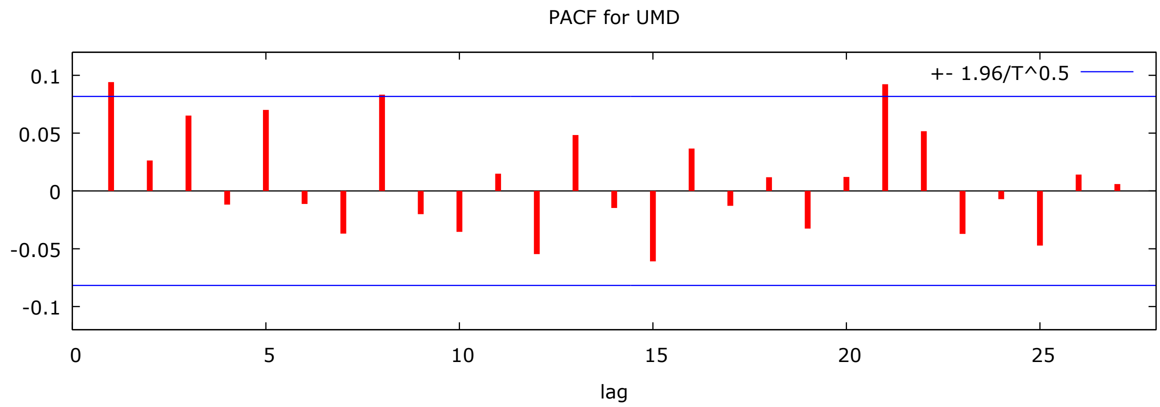


Figure A 5.23 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on the liquidity factor (emerging African market)

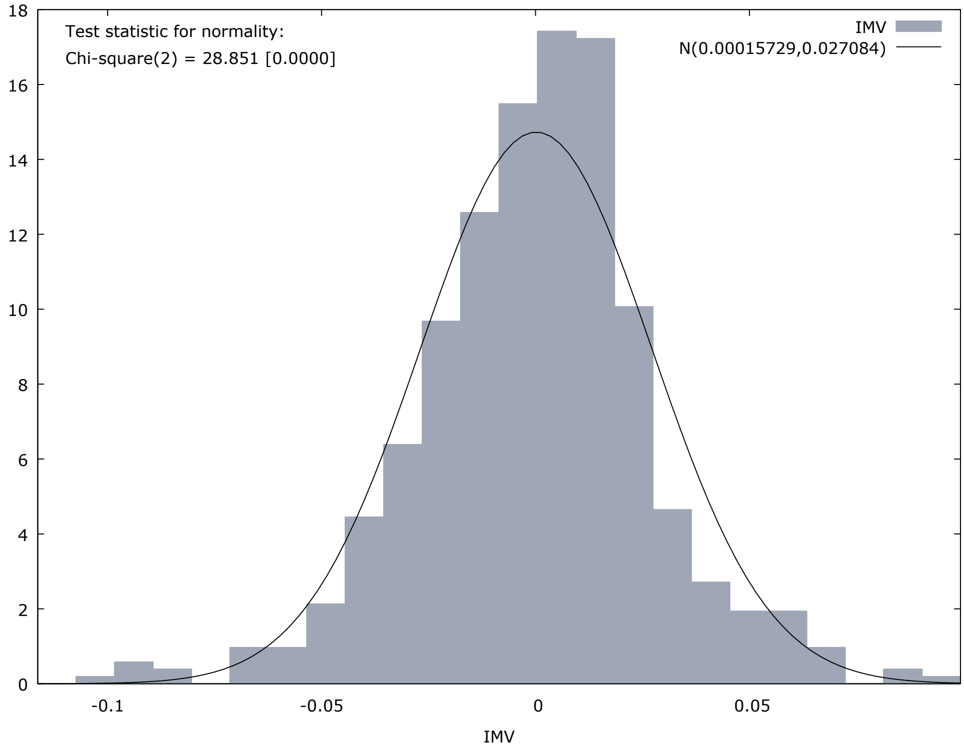
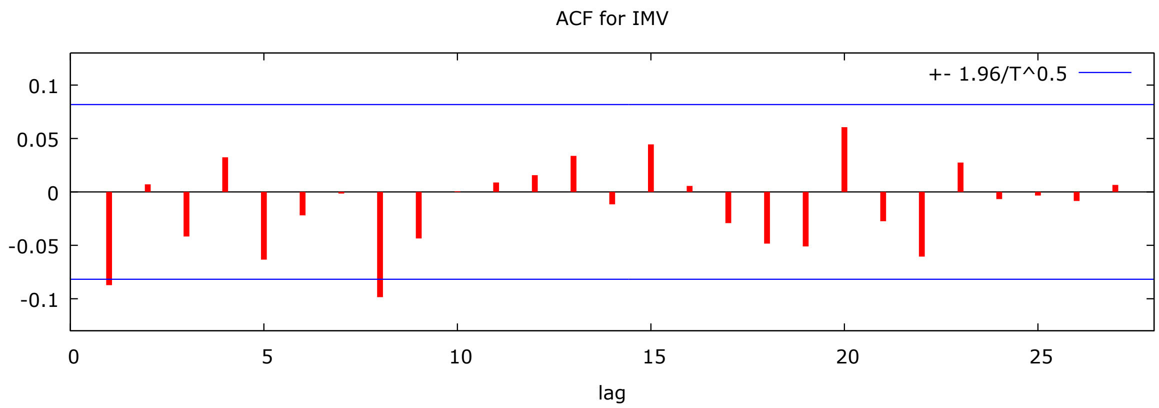


Figure A 5.24 Liquidity portfolio correlogram (emerging African market)



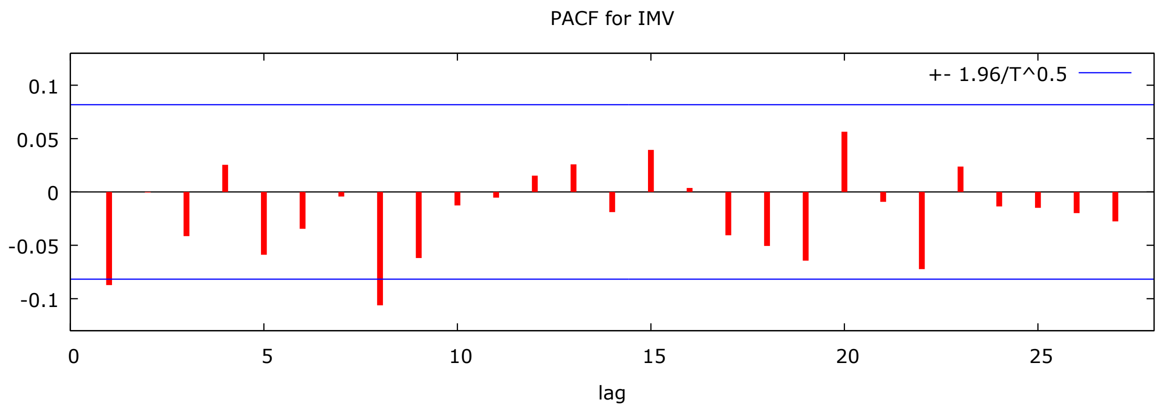


Figure A 5.25 Frequency distribution with Doornik-Hansen test for normality for the skewness (S_i) measure (emerging African market)

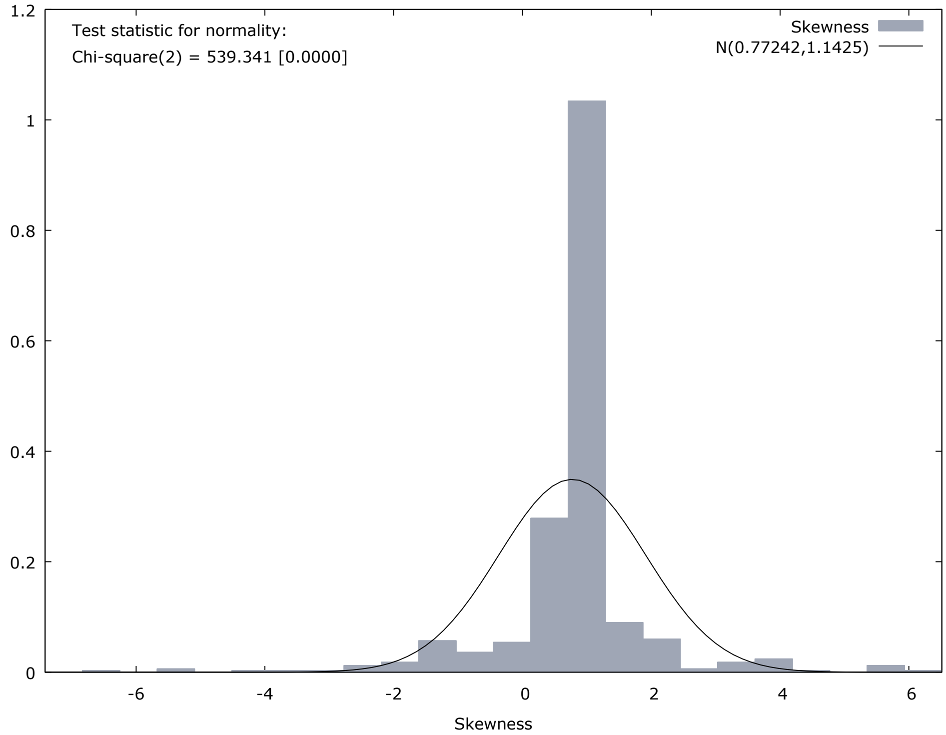


Figure A 5.26 Skewness (S_i) measure correlogram (emerging African market)

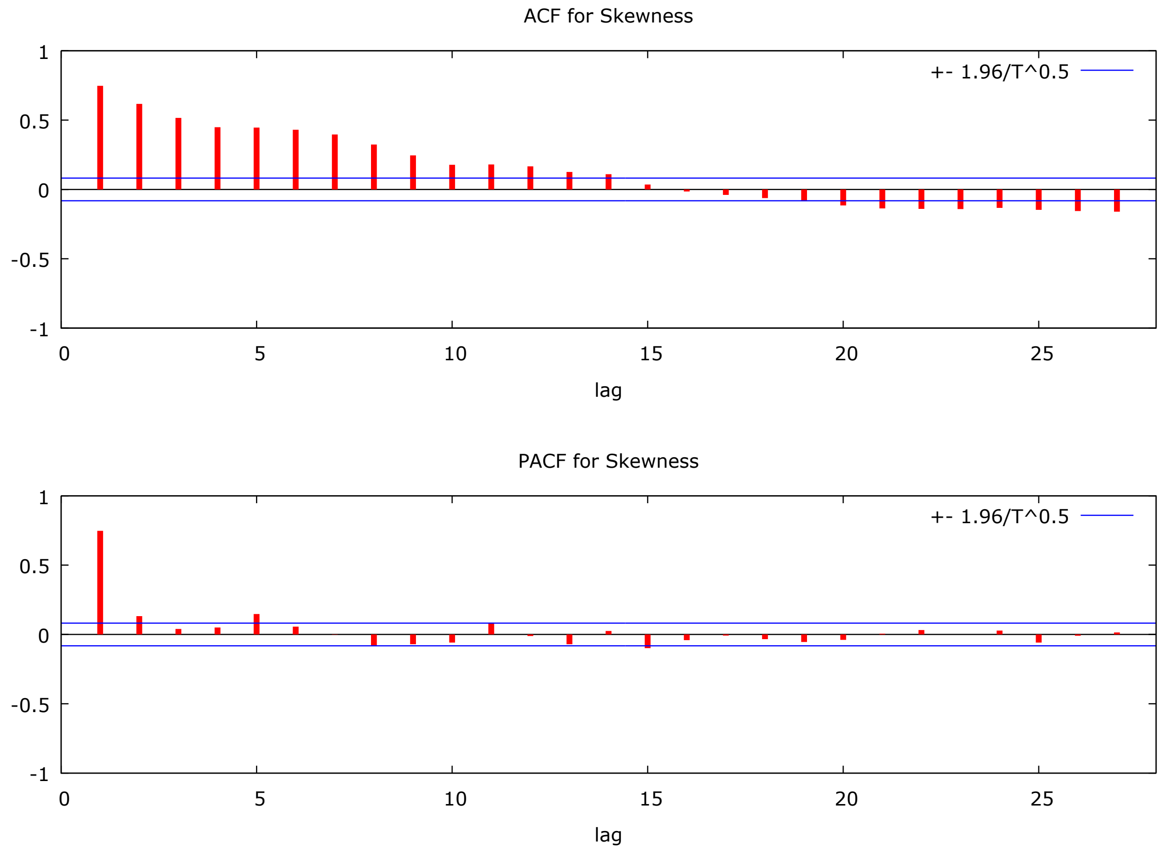


Figure A 5.27 Frequency distribution with Doornik-Hansen test for normality for the kurtosis (K_i) measure (emerging African market)

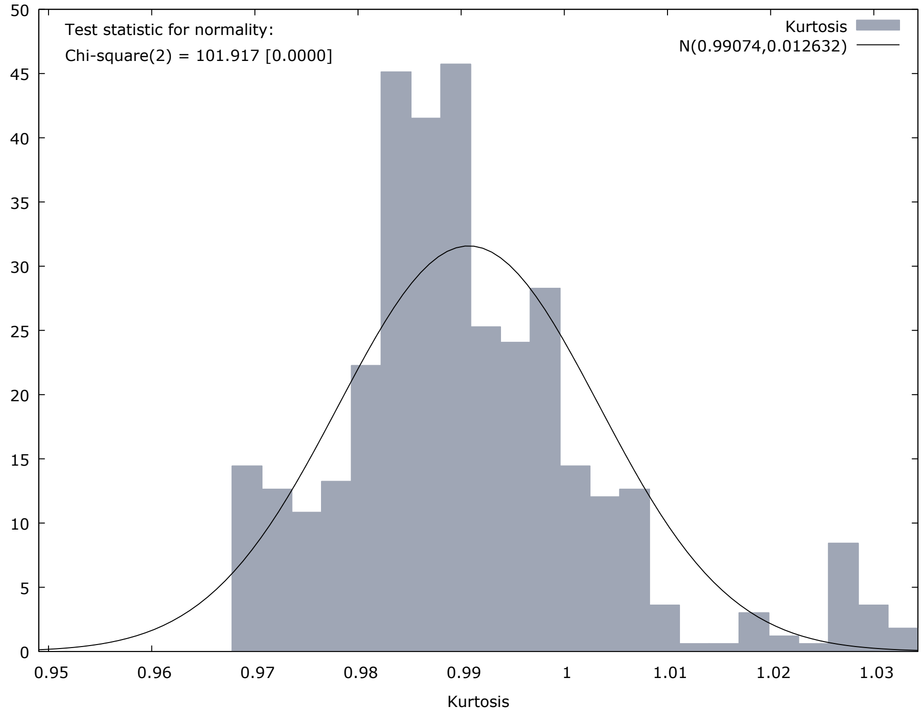
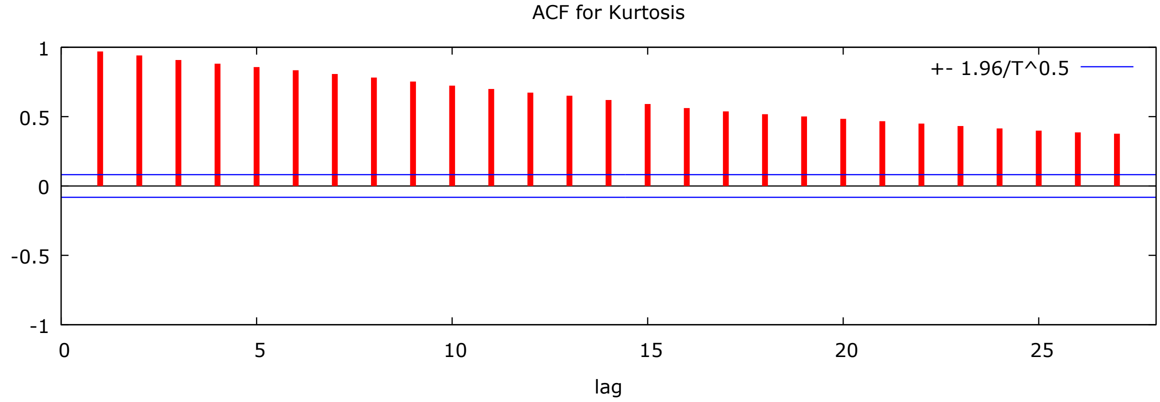
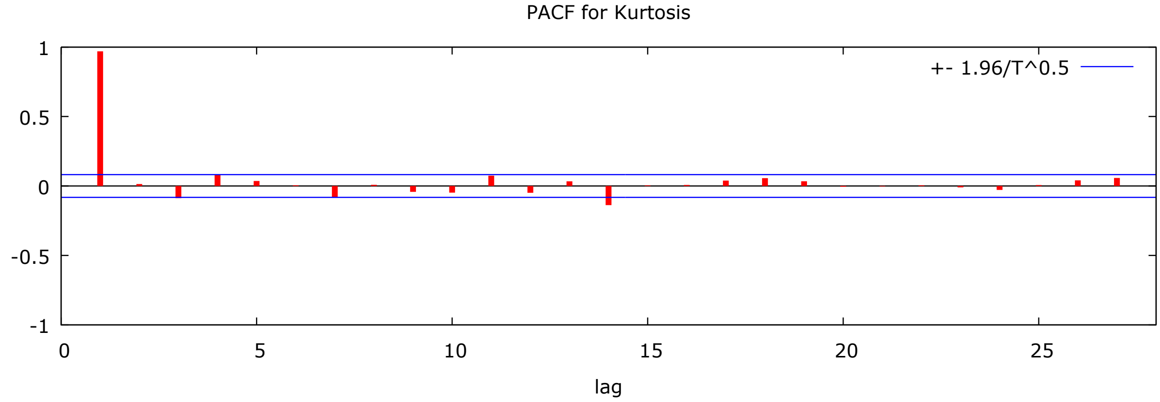


Figure A 5.28 Kurtosis (K_i) measure correlogram (emerging African market)





Emerging market excluding South Africa index

Figure A 5.29 Frequency distribution with Doornik-Hansen test for normality for the market portfolio (emerging African market excluding South Africa)

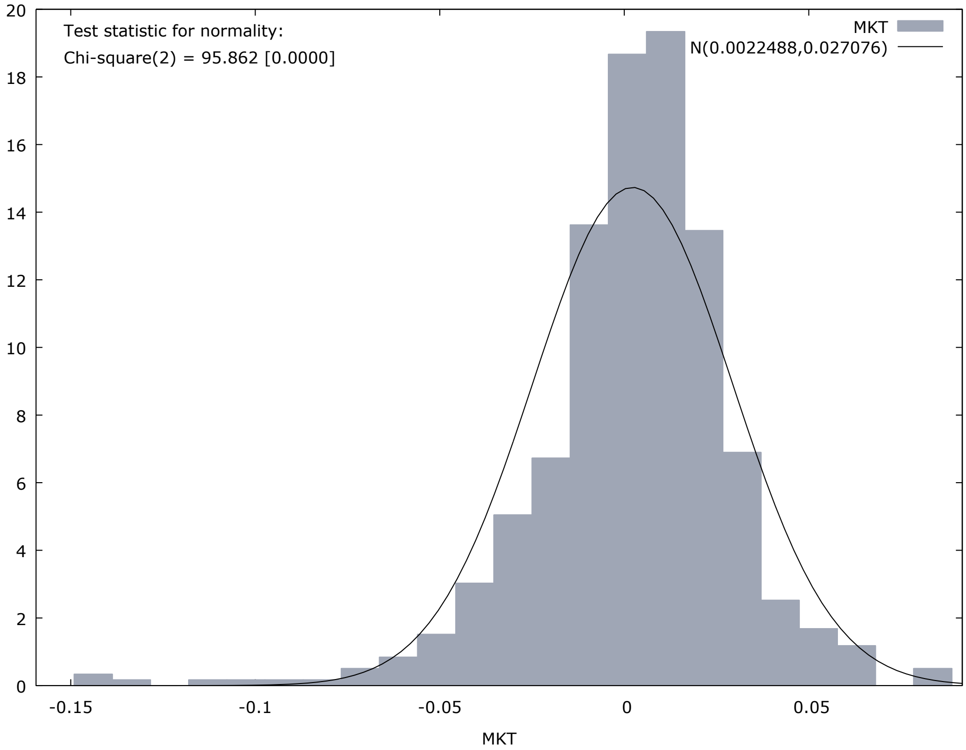


Figure A 5.30 Market portfolio correlogram (emerging African market excluding South Africa)

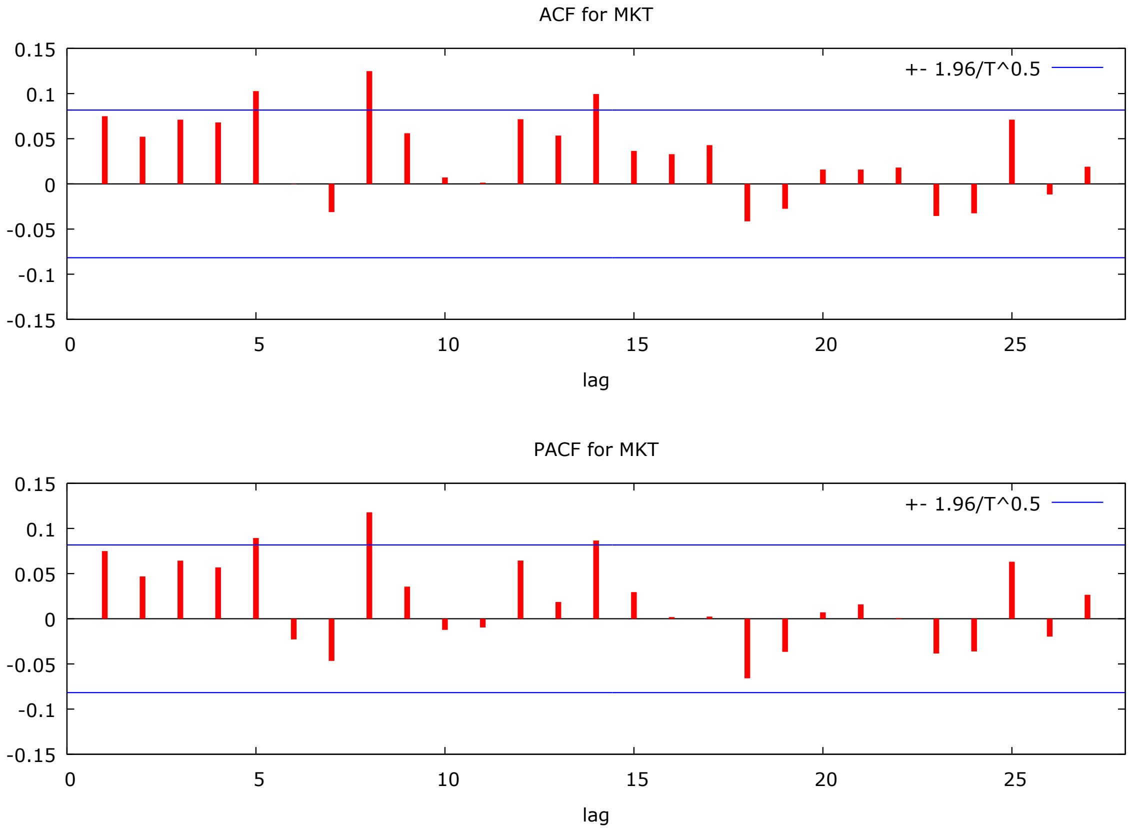


Figure A 5.31 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on size (emerging African market excluding South Africa)

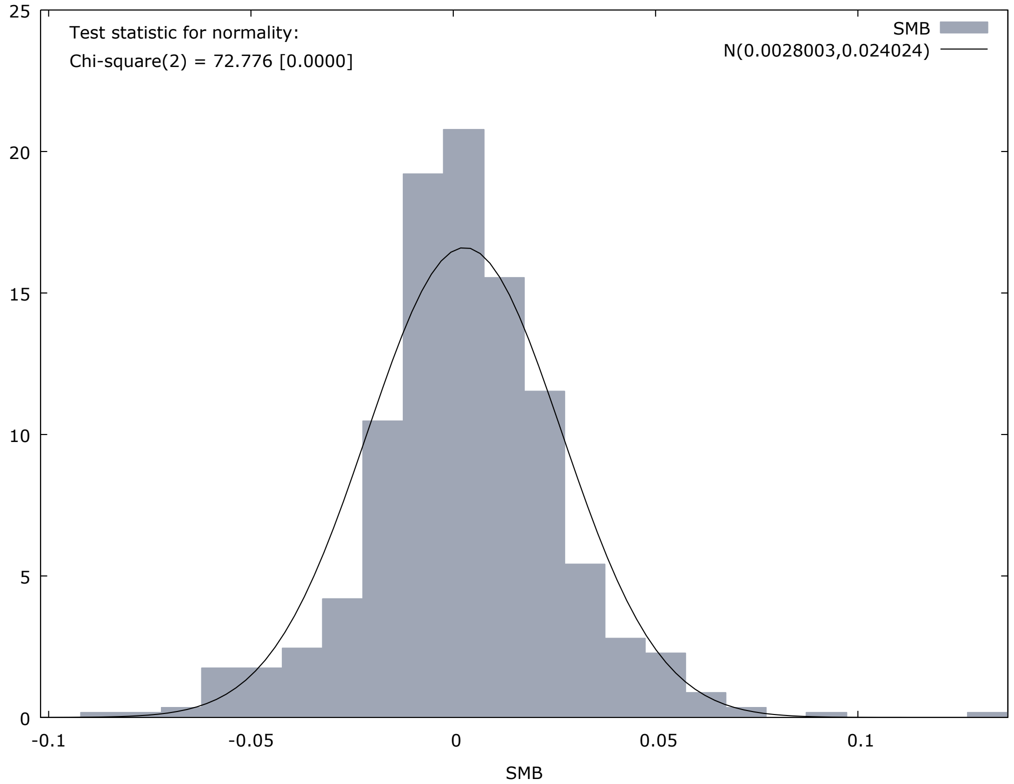
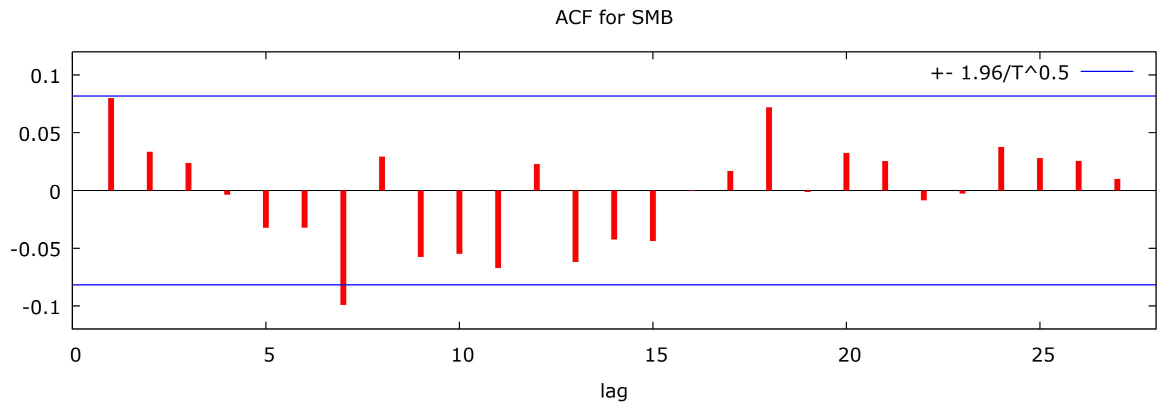


Figure A 5.32 Size portfolio correlogram (emerging African market excluding South Africa)



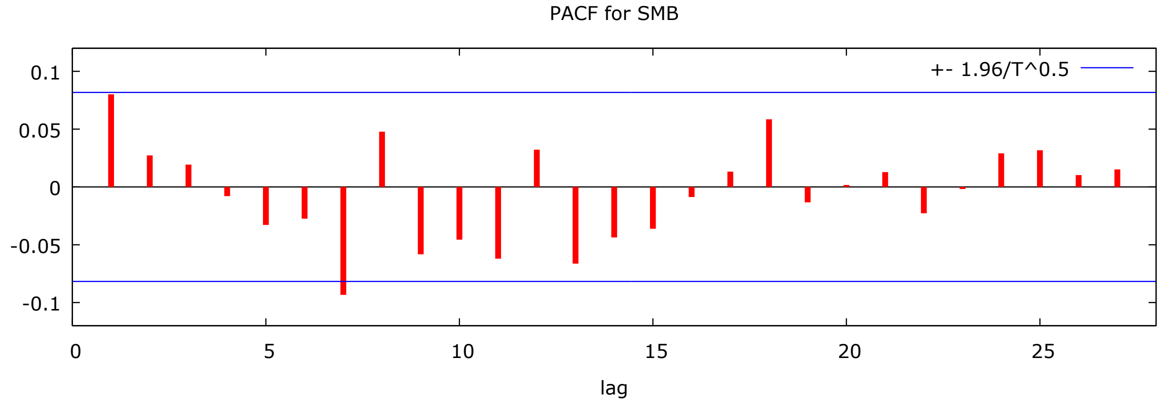


Figure A 5.33 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on value (emerging African market excluding South Africa)

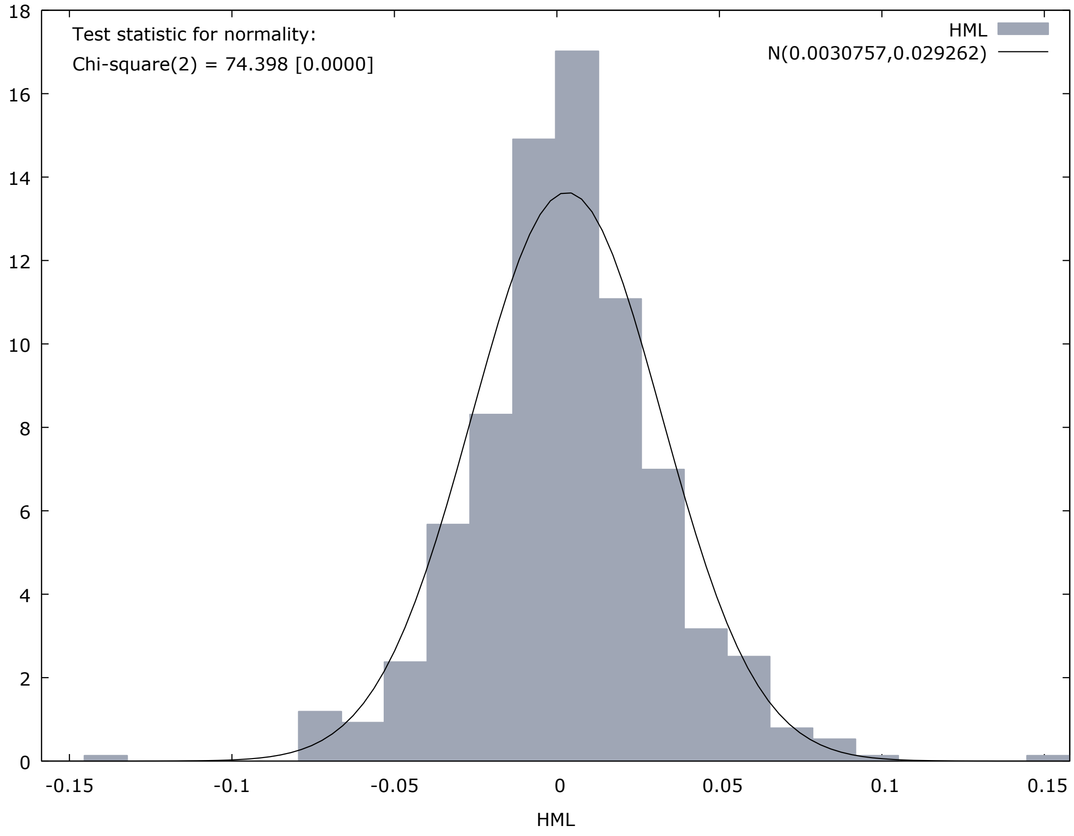
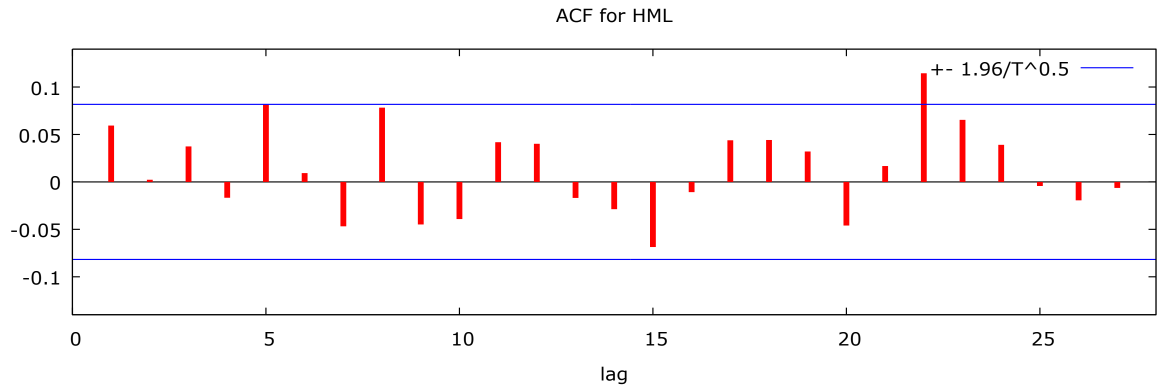


Figure A 5.34 Value portfolio correlogram (emerging African market excluding South Africa)



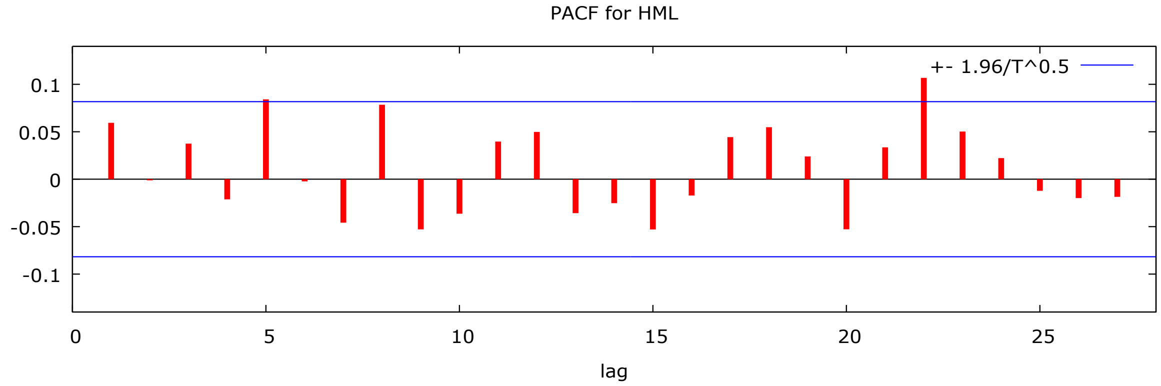


Figure A 5.35 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on the momentum factor (emerging African market excluding South Africa)

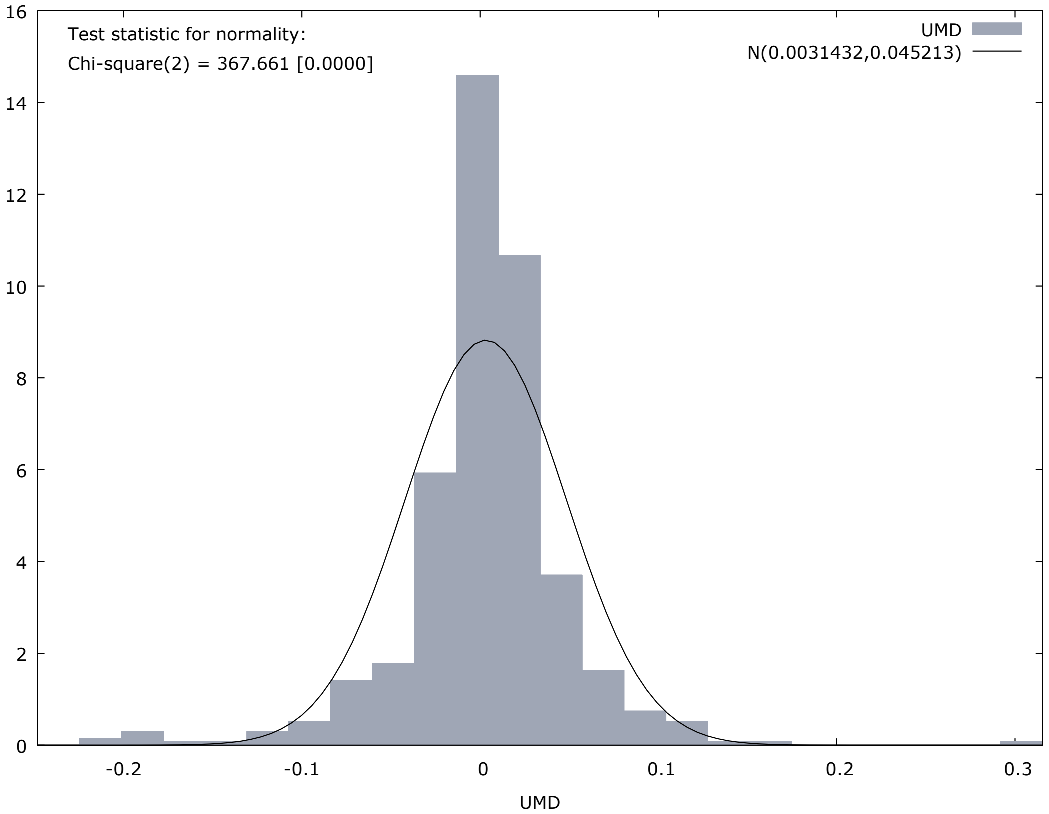
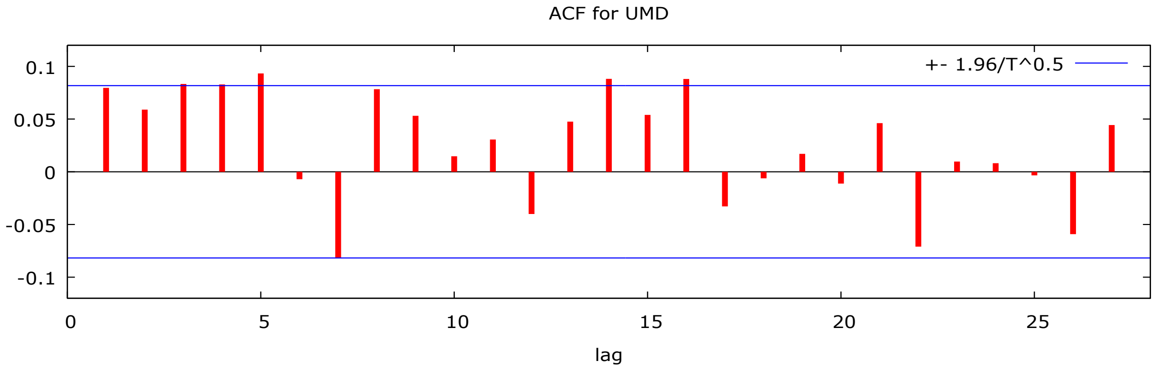


Figure A 5.36 Momentum portfolio correlogram (emerging African market excluding South Africa)



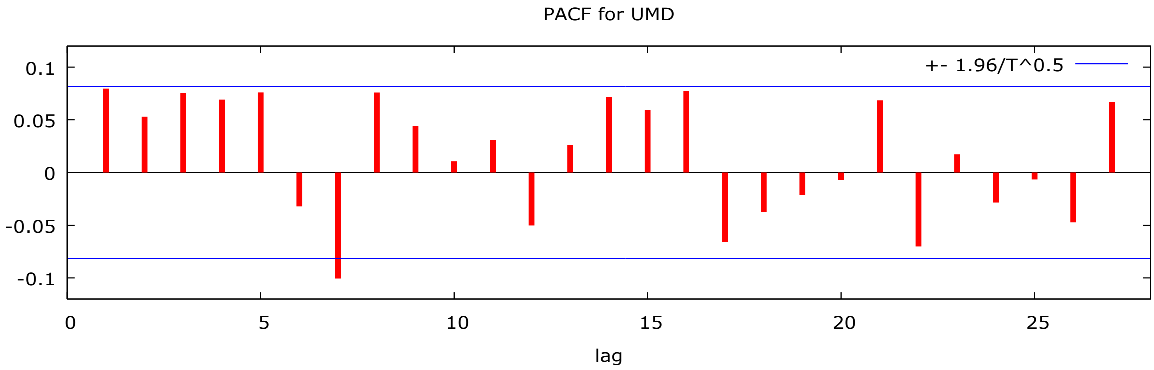


Figure A 5.37 Frequency distribution with Doornik-Hansen test for normality for the portfolio formed on the liquidity factor (emerging African market excluding South Africa)

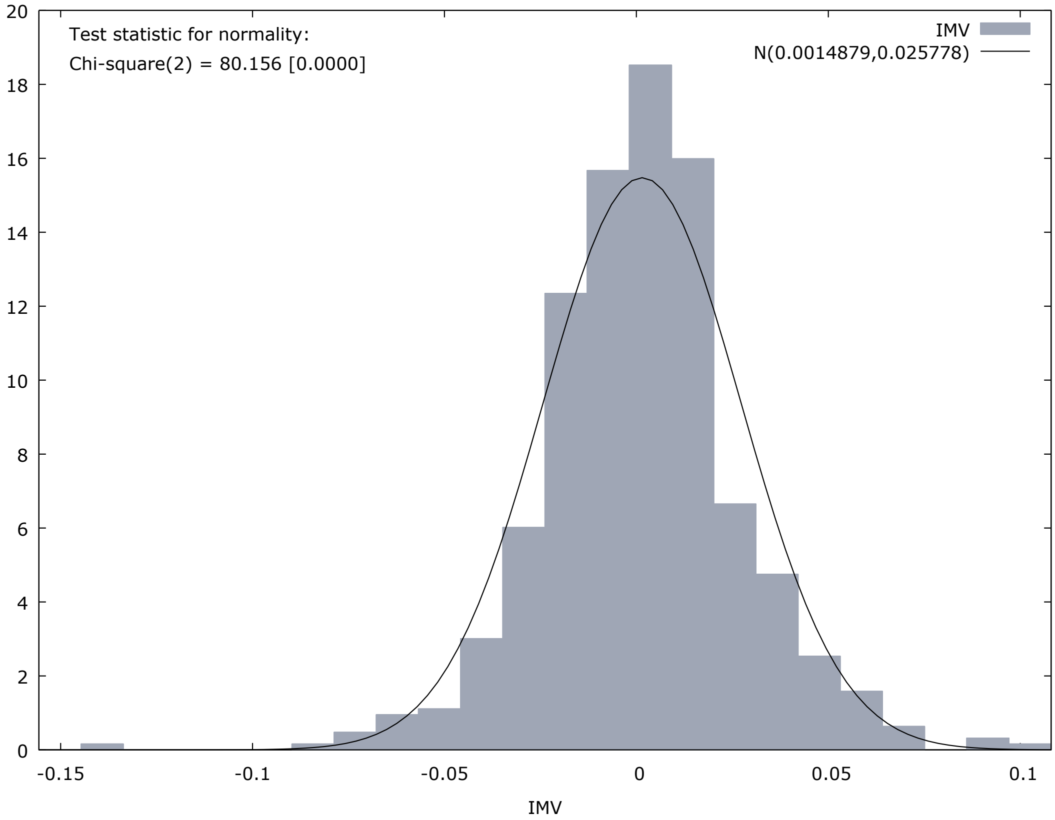


Figure A 5.38 Liquidity portfolio correlogram (emerging African market excluding South Africa)

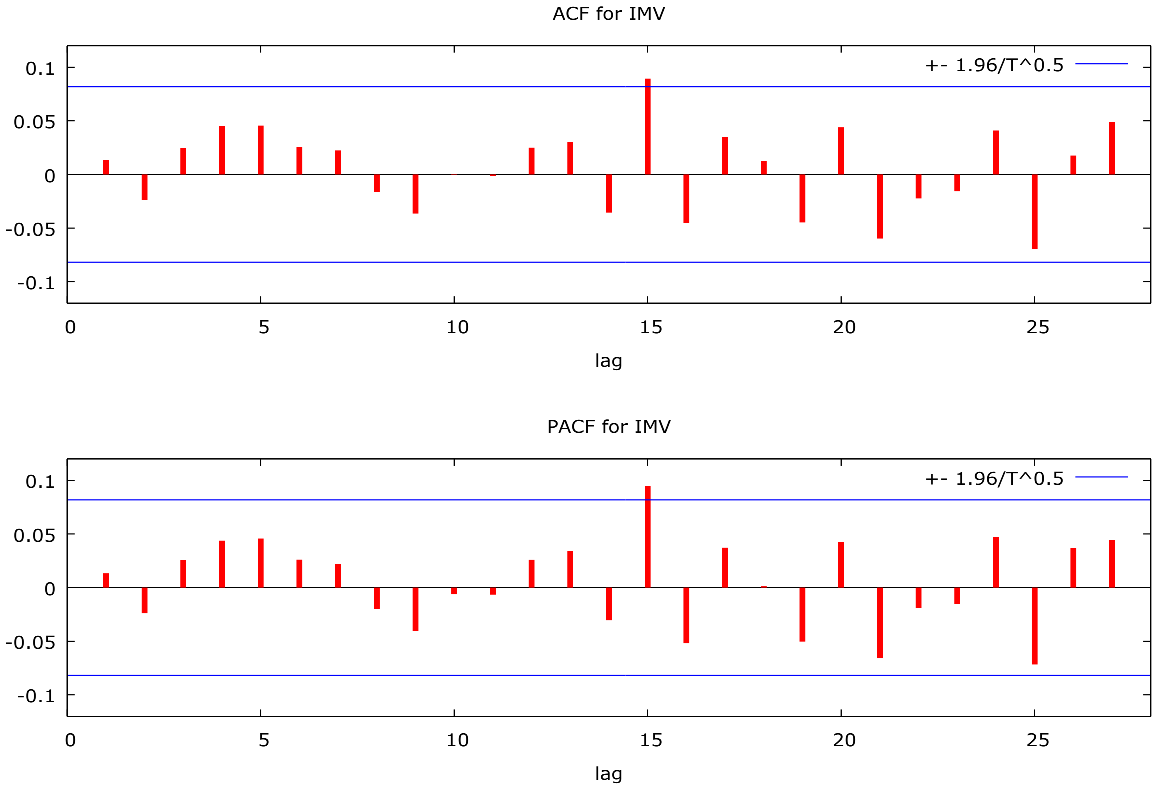


Figure A 5.39 Frequency distribution with Doornik-Hansen test for normality for the skewness (S_i) measure (emerging African market excluding South Africa)

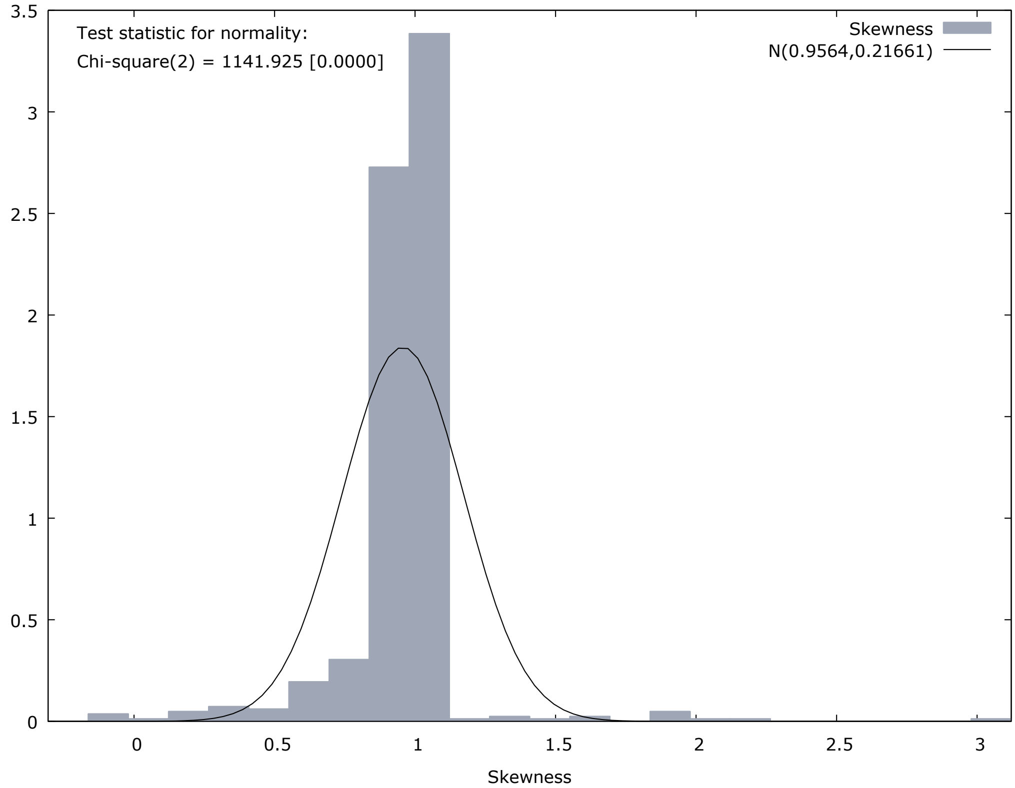
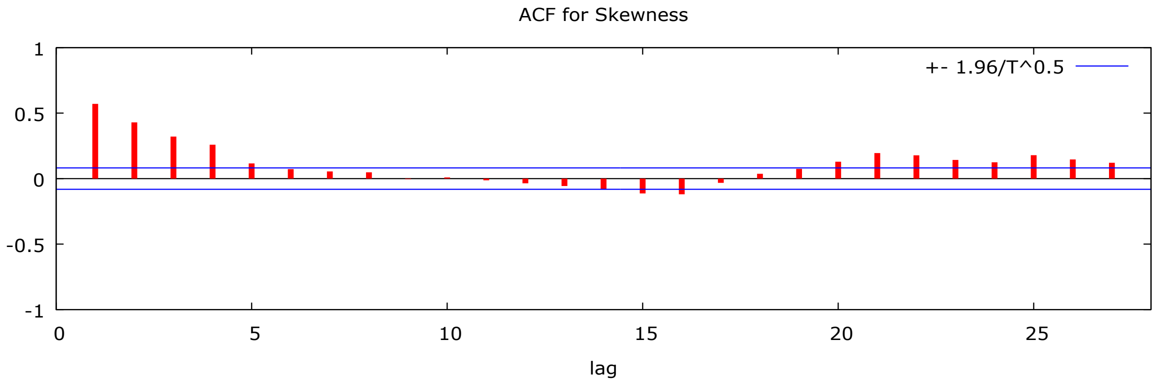


Figure A 5.40 Correlogram for the skewness (S_i) measure (emerging African market excluding South Africa)



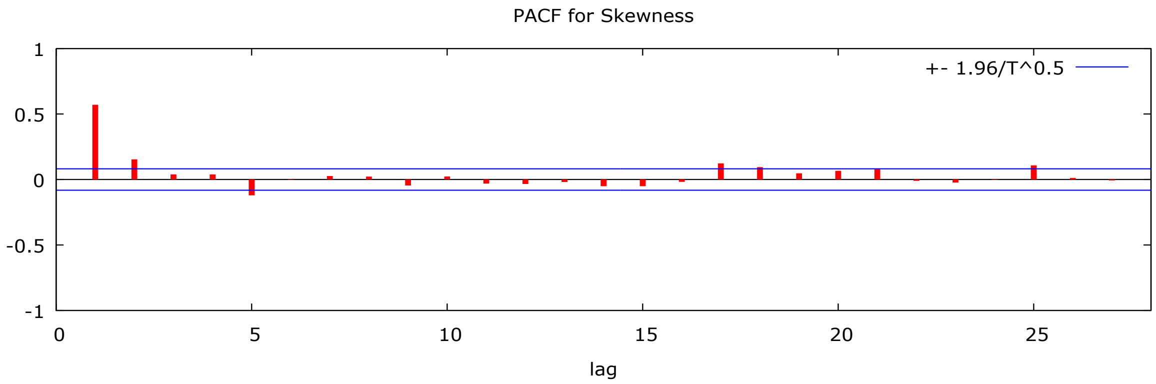


Figure A 5.41 Frequency distribution with Doornik-Hansen test for normality for the kurtosis (K_i) measure (emerging African market excluding South Africa).

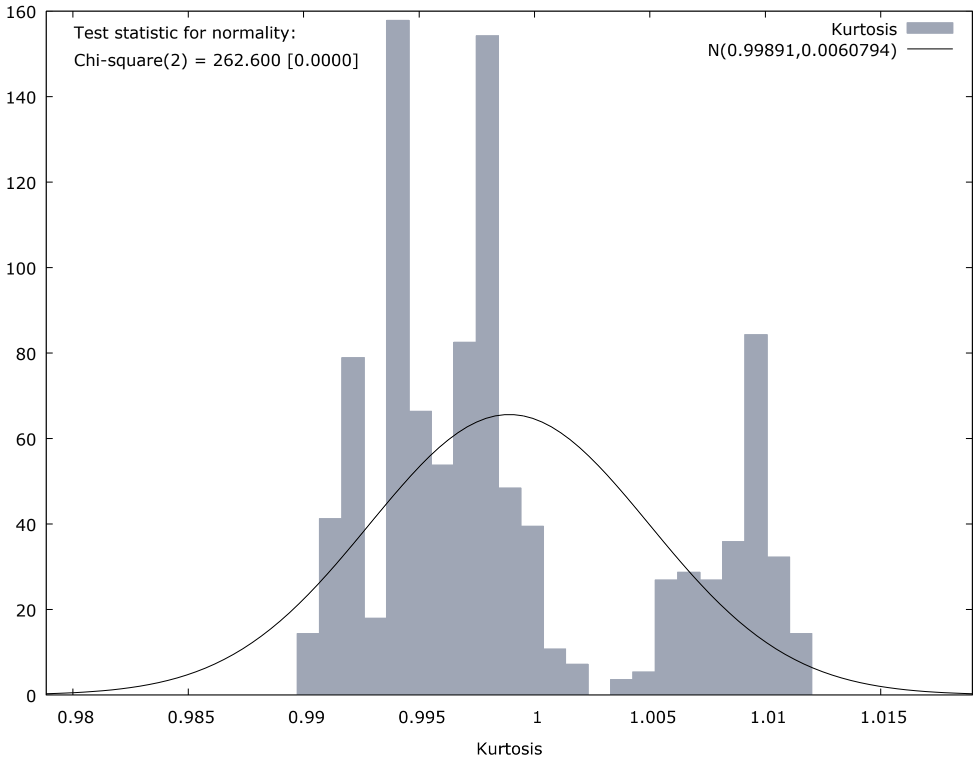
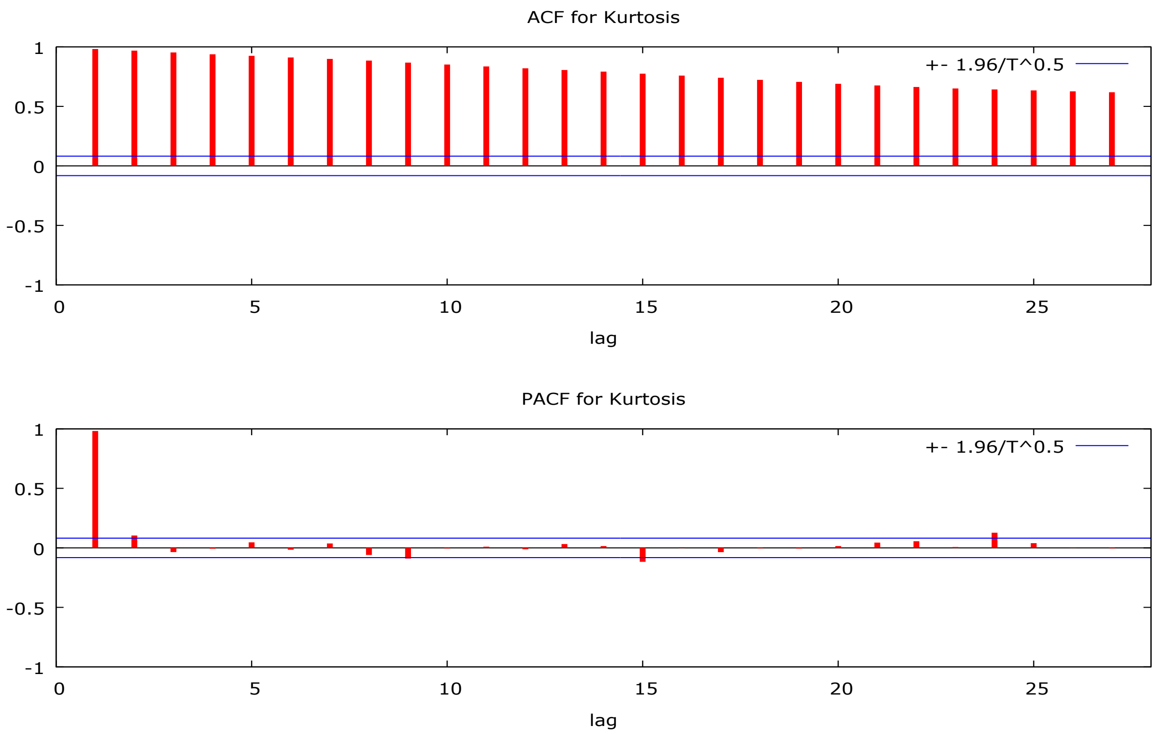


Figure A 5.42 Correlogram for the Kurtosis (K_i) measure (emerging African market excluding South Africa)



6 DISCUSSION OF FINDINGS

6.1 Introduction and structure of chapter

The objectives of this chapter are threefold. The first objective is to draw some conclusion on which model performs best in each of the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market and why they differ across the sample. To achieve this, I compare the performance of the Sharpe-Lintner CAPM, the Fama-French three-factor model, the Carhart four-factor model, the liquidity-augmented variants and also a liquidity- and higher-moments augmented four-factor model.

The second objective is to analyse differences in the importance of beta, size, value, momentum, liquidity, coskewness and cokurtosis within the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market, as highlighted in Chapter 5.

The third objective is to evaluate the impact of contagion (contagion effect resulting from the financial crisis and the Arab Spring) within the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market, and analyse the rationale for any differences.

Section 6.2 discusses Sharpe-Lintner CAPM, Section 6.3 assesses the Fama-French three-factor model while Section 6.4 evaluates the Carhart four-factor model. The effect of liquidity is discussed in Section 6.5, while the effect of contagion in the liquidity-augmented models is analysed in Section 6.6. Section 6.7 investigates the performance of the higher-order moment and liquidity-augmented four-factor model. Section 6.8 evaluates the importance of beta within the asset-pricing models. Section 6.9 analyses the size effect while Section 6.10 assesses the importance of the book-to-market value factor. The importance of the momentum effect is discussed in Section 6.11 while the explanatory power of the liquidity factor is analysed in Section 6.12. Higher-moment effects are discussed in Section 6.13 while the importance of contagion effect is highlighted in Section 6.14.

6.2 Sharpe-Lintner CAPM

In evaluating the performance of the models, I replicate the methods in Lam and Tam, where the "better" model is the model with the most insignificant alpha terms across the markets and the highest adjusted R^2.

The Sharpe-Lintner one-factor CAPM model performs well in the emerging African market excluding South Africa, as the Jensen alpha terms, α_i, in this market was positive and insignificant. However, the model performs poorly in the South African market, the emerging African market and the frontier African market, as the Jensen alpha terms, α_i, were significant. In the South African market and the emerging African market the alpha terms were negative and significant at the 5% and 10% levels, respectively, indicating a risk premium that is less than predicted by the CAPM. But in the frontier African market, the alpha term was positive and significant at the 5% level, indicating a risk premium higher than predicted by the CAPM.

There are some explanations for this deviation of the CAPM in these African markets. One of these is the role of missing risk factors within the models. Fama and French (1993) also identified that the source of CAPM alpha deviation from zero is actually missing risk factors, which has led to their empirical examination of multifactor asset pricing. They found that the intercept of their three-factor model was close to zero; hence they conclude that missing risk factors in the CAPM are the sources of the deviation. The explanation for this significant alpha could be traced to investment strategies in these markets through preference for investment in highly profitable firms, overreacting to good and bad news, assuming trends in stock prices and extrapolating past growth rates too far into the future, as also seen within the South African market. These are aided by poor information dissemination and relatively underdeveloped institutional environment within which the financial markets operate in the less-developed African markets, when compared with South Africa and the developed markets. Another important factor that will be more pronounced within this market is the effect of time variation resulting from macroeconomic factors.

On the other hand, MacKinlay (1995) identified that non-zero intercepts may not be solely due to missing risk factors, but to firm specific factors. He identified the possible impact of market friction and liquidity constraints on intercepts of CAPM tests. Hence there may have been some sector-specific factors within the basic materials indices in the South African market, the emerging African market and the frontier African market, which may have led to the significant intercepts. Although this sector is one of the most liquid in the African continent, given that most of the countries are resource-driven, the equities market in the entire continent is still quite illiquid when compared with developed markets. This will give rise to problems of illiquidity and market friction, as identified in MacKinlay (1995).

Another explanation comes from the work of Conrad and Kaul (1993), which considers the possibility that biases in computed returns explain the deviations. They note that the implicit portfolio rebalancing in most analysis biases measured returns upwards, leading to overstating returns and CAPM deviations. This is not the case within our study because all indices were rebalanced using the same method, but results differ.

Lo and MacKinlay (1990) highlight that this deviation may due to data-snooping. They argue that deviations are a result of data-snooping that is mainly due to the grouping of assets with common disturbance terms. However, this again is not a problem within this study because some of the results reflect the theoretical expectation, while some do not, and in both cases the results are stated. Although it is difficult to quantify and adjust for the effect of data-snooping biases, MacKinlay (1995) identified that avoiding the sample selection bias problem discussed in Kothari, Shenken and Sloan (1994) may be a good way to ensure that data-snooping is avoided. This study has adjusted for selection bias (survivorship bias) as shown in Chapter 3.

In comparing the performance of the CAPM and the Fama-French model, Bartholdy and Peare (2005) compared the estimates of expected returns based on each model to identify the "best" possible estimate. Using a practitioner approach, they defined the best possible estimate using the R^2 (goodness of fit). R^2 measures how much the estimation procedure explains the difference in individual stock index return. Hence the best refers to the model and data that result in the highest R^2. When the goodness of fit (R^2) of the model is analysed across the markets, I see some differences, with an adjusted R^2 of 37.8% in the emerging African market and 53.6% in the emerging African market excluding South Africa. The adjusted R^2 in the South African market and frontier African market were 36% and 2.4%, respectively. Hence I can conclude that CAPM performs best within the emerging African market excluding South Africa. The low R^2 in these markets is similar to those reported in Hearn, Piesse and Strange (2010) where they found adjusted R^2 as low as 0.0995.

The performance of the CAPM in these markets will most likely be different to the performance of the multifactor models, hence the better performance of CAPM in the emerging African market excluding South Africa is limited to the standard CAPM.

6.3 Fama-French three-factor model

Following the findings in Fama and French (1993), which indicate that the intercept of their three-factor model was close to zero and conclude that missing risk factors in the CAPM are the sources of the deviation, this study analysed the Fama-French three-factor model within the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market.

The results show a negative and insignificant alpha term for the South African market and the emerging market excluding South Africa, which is in line with findings in Hearn and Piesse (2009), who indicate that within the African market alpha terms are not statistically different from zero. However, this study finds significant alpha terms for the emerging and frontier African market indices (alpha is negative and positive for the emerging and frontier African market indices, respectively). This indicates that given the beta in the emerging African market, the basic materials index within this market returns less than the market index. On the other hand, the basic material index returns in the frontier African market are higher than the market returns, given the beta.

This indicates that the three-factor model performs well in the South African market and the emerging African market excluding South Africa, while performing poorly in the emerging and frontier African markets. The significant alpha term in the emerging African market and the frontier African market could be an indication of an inefficient market. This divergence in performance of this model is due to the structure of these markets and their degree of integration with developed markets, given that the Fama-French three-factor model was developed within the developed markets. South Africa, for example, is the closest integrated market to the developed markets, hence the good performance of this model in this market is not surprising.

More surprising, though, is the good performance of the model within the emerging African market excluding South Africa against the poor performance of the model when South Africa is included within the emerging African market. This is due to the interaction between the South African market and the Egyptian and Moroccan markets, resulting from the varying degree of integration with developed financial markets. As seen in Collins and Biekpe (2003), the South African market is the most integrated of the African markets; although other countries such as Egypt and Morocco are becoming more integrated, they have not yet reached the weightiness of the South African market.

Clearly, this study suggests that the performance of the Fama-French three-factor model depends on the characteristics of the surveyed market. This is related to the structure of the index, i.e. the emerging African market index that includes South Africa, Egypt and Morocco. Assefa and Mollick (2014) also find significant differences in their result when South Africa is excluded from their sample of African countries. The significant alpha term for the emerging and frontier African markets may also be due to the interaction between the markets that make up the index and/or some macroeconomic or exogenous factors. The effect of these will vary depending on the degree of integration, as the more integrated the market is with global markets, the less the price of risk. There seems to be a general consensus on this, as seen in Stulz (1999), Bekaert and Harvey (2000) and Errunza and Miller (2000).

As stated in Fama and French (1996), the economic interpretations of the findings in Fama and French (1993) has remained contentious, with some agreeing that the model describes return, but argue that it is investor irrationality that prevents the three-factor model from collapsing into the CAPM, as seen in Lakonishok, Shleifer and Vishny (1994) and Haugen (1995). Others argue that CAPM anomalies are due to survivorship bias, data-snooping or poor proxies for market portfolio, as seen in Black (1993). Fama and French (1996) do, however, make the case for the multifactor model by arguing that the standard deviation for their HML portfolio is high (13.11%) and similar to the standard deviation for the MKT and SMB portfolios (16.33% and 15.44%, respectively).

They also find similar annual premiums for the HML, MKT and the SMB portfolios, indicating that the return on the HML is not a certainty, as indicated in Haugen (1995). This disputes the rational pricing explanation of multifactor models as seen in Lakonishok, Shleifer and Vishny (1994). Indeed, the average returns and standard deviations of our portfolios confirm the findings in Fama and French (1996). The argument on survivorship bias, data-snooping and poor proxies for market portfolio are excellently addressed in Fama and French (1996). While our findings are consistent with the process in Fama and French (1993, 1996), the performance of the Fama-French three-factor model depends on the surveyed market.

Using the "best" possible estimate identified Bartholdy and Peare (2005), I compare the R^2 (goodness of fit) for the markets. The adjusted R^2 for the South African market and the emerging African market were 54.81% and 38.40%, respectively, while the adjusted R^2 for the emerging African market excluding South Africa and the frontier African market were 55.15% and 3.12%, respectively. Clearly the R^2 for the emerging African market excluding South

African was the highest, and with an insignificant intercept as identified previously. At 54.81%, the R^2 for the South African market is pretty close to that of the emerging African market excluding South Africa, and with an insignificant alpha term too; hence the three-factor model performs well in the emerging African market excluding South Africa and the South African market.

The adjusted R^2 is low in the African market overall and specifically in the frontier African market compared to the findings in Fama and French (1993), because of the difference in our dataset compared to that in Fama-French. This indicates that the models are less applicable to the African stock market. Lam and Tam (2011) find a similar difference in their adjusted R^2 for the same reason.

6.4 Carhart four-factor model

Following Carhart (1997), this study analysed the performance of the four-factor model within the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market. The results show that the additional variables in the model account for the outstanding returns variation in the South African market and the emerging African market excluding South Africa, with the alpha terms insignificant for both markets. However, the model performs poorly within the emerging African market (with a negative and significant alpha term) and the frontier African market (with a positive and significant alpha term).

Most of the criticisms of the Fama and French (1993) model apply to the Carhart (1997) model, too, due to the multifactor nature of both models. Hence, the Carhart model also disputes the rational pricing explanation of multifactor models as seen in Lakonishok, Shleifer and Vishny (1994). Appropriate adjustment has also been made to eliminate survivorship bias. The results demonstrate that the explanatory power of the model depends on the surveyed market.

Using the "best" possible estimate identified in Bartholdy and Peare (2005), we compare the R^2 (goodness of fit) for the markets. The adjusted R^2 for the South African market and the emerging African market were 54.86% and 38.51%, respectively, while the adjusted R^2 for the emerging African market excluding South Africa and the frontier African market were 61.48% and 5.13%, respectively**.** Again, this clearly shows that the Carhart four-factor model performs significantly better in the emerging African market excluding South Africa. The increase of the adjusted R^2 between the three-factor and the four-factor model within the South African market and the emerging African market does not adequately justify the inclusion of the momentum factor, especially given that the momentum factor is insignificant in these markets. The adjusted R^2 increased by 0.0572% and 0.179% in the South African market and the emerging African market, respectively, hence the effort in forming this variable is not justified in these markets.

6.5 Liquidity-augmented Carhart four-factor model

This section analyses the equilibrium asset pricing with liquidity risk, which is the risk arising from unprecedented changes in liquidity over time. We show that the model worked well in explaining realised returns, with non-significant alpha terms, in the South African market and the emerging African market excluding South Africa. The alpha terms remained significant in the emerging African market and the frontier market index.

When compared with the four-factor models not augmented by the liquidity factor, the inclusion of the liquidity factor in all four market samples did not improve the alpha term, although the liquidity factor was significant within the South African market and the emerging African market excluding South Africa.

The inclusion of the liquidity variable within the South African market has resulted in a significant increase in the explanatory power to 57.07% adjusted R^2, compared with 54.56% for the four-factor model not augmented by the liquidity factor. However, within the emerging African market, the adjusted R^2 was unchanged at 38.51% compared with 38.51% before including liquidity. The improvement in the adjusted R^2 in the emerging African market excluding South Africa was marginal, with a 0.2925% increase. I also observe an increase in adjusted R^2 within the frontier African market, with an increase from 5.13% to 5.69%.

The improvements in the R^2 observed here, although quite marginal, are also consistent with findings in the literature, as seen in Acharya and Pedersen (2003), who find that liquidity-augmented CAPM performs better than the standard CAPM in terms of its R^2 for cross-sectional returns and p-values in specification tests.

6.6 Liquidity-augmented four-factor model in the presence of contagion

This section analyses the effect of contagion on the performance of the liquidity-adjusted four-factor models in the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market. The results show that the model worked well in explaining realised returns, with insignificant alpha terms, in the South African market, the emerging African market and the emerging African market excluding South Africa; however, the frontier market index had a significant alpha term.

The alpha term for the South African market and the emerging African market excluding South Africa remains insignificant when compared to the liquidity-augmented models that do not include a contagion dummy. The alpha term for the emerging African market became significant with the introduction of the contagion dummy, while the significance level for the alpha terms increased from the 5% level to the 1% level within the frontier African market. This highlights the impact of time variation on the emerging African market index.

This is also supported by the significant contagion variable within all four markets.

The performance of this model alludes to the importance of time variation in estimates of the CAPM. This is also consistent with recent developments in asset pricing that insist that asset-pricing models should allow for time variation in estimated beta, as stated in Groenewold and Fraser (1999). Others who model the conditional distribution of returns include Ferson and Harvey (1999) and Lettau and Ludvigson (2001). With an insignificant alpha term and the highest R^2 for the liquidity-augmented four-factor model that accounts for the contagion effect, I conclude that the liquidity-augmented four-factor model that accounts for the contagion effect performs best within the South African market, the emerging African market and the emerging African market excluding South Africa. Hence I recommend this model within these markets.

6.7 Higher-order moments and liquidity-augmented Carhart four-factor model

This section analyses the effect of higher-order moments on the performance of the standard CAPM, the three and four-factor models in the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market, when the models are augmented by the liquidity factor and the contagion variable. The results show that the models worked well in explaining realised returns, with insignificant alpha terms, in the South African market and the frontier African market; however, the emerging African market index and the emerging African market excluding South Africa had significant alpha terms.

When compared to the liquidity-augmented models, the introduction of skewness and kurtosis within the South African market has not made any difference as the Jensen alpha term continues to be insignificant. However, within the emerging market and the emerging African market excluding South Africa, the introduction of higher moments has made the alpha term significant at the 1% level for the liquidity-augmented three-factor model, when it was insignificant prior to introduction. When higher moments are included in the liquidity-augmented four-factor model of the frontier African market, the alpha term becomes insignificant. This demonstrates that skewness and kurtosis are important in explaining realised returns in the frontier African market.

In regard to the performance of the models as measured by the adjusted R^2, the adjusted R^2 for the South African market was 57.36% compared to the 57.49% for the liquidity-augmented four-factor model. Hence I conclude that the higher-moment augmented model does not perform better in the South African market. The adjusted R^2 for the emerging African market was 39.82% compared to 39.35% when the model excludes higher moments. Hence I can infer that the higher-moment augmented models fit the emerging African market data quite well compared to models that do not account for the effect of higher moments, but I cannot conclude that it performs better, as the alpha term becomes significant upon introduction.

For the emerging African market excluding South Africa, the adjusted $R^2$was 62.35% compared to 62.03% when the model does not account for higher moments, indicating that the higher-moment augmented model fits the emerging African market excluding South Africa data quite well rarther than models that do not include higher moments, but due to the significant alpha term, I cannot conclude that this model is better. The adjusted R^2 within the frontier market was 8.28%, compared to 7.89% for the liquidity-augmented four-factor model, indicating that higher-moment augmented models fit the data in the frontier African market better than models that do not account for higher moments. Hence, with an insignificant alpha term, I conclude that the higher moments and liquidity-augmented four-factor model be applied to the frontier African market. Our findings are also consistent with those in Harvey and Siddique (2000), who identify that the success of any given multifactor model depends substantially on the methodology and data used to empirically test the model.

6.8 Beta in the African market

The single-factor CAPM of Sharpe (1964) and Lintner (1965) identifies the importance of beta in asset pricing. This has been supported by many authors and disputed by some, but remains popular with practitioners, as stated in Bruner et al. (1998) and Graham and Harvey (2001)**.** However, Fama and French (1992) found the relationship between expected return and beta to be too flat and statistically insignificant. Also, Frazzini and Pedersen (2010) find consistent returns to betting against beta, while Moskowitz, Ooi and Pedersen (2012) show the presence of global time-series momentum with Koijen et al. (2013) documenting global carry returns.

This study does, However, find that beta is important across all models and in all markets studied, as shown in Table 6.1. Within the South African market, beta for the standard CAPM was 1.054 and significant at the 1% level, indicating that the South African basic materials index is riskier than the market index. This is expected because of the high volatility in the South African basic materials index resulting from industry-specific risks, political risks, financial risks and economic risks as identified in Hassan et al. (2003). Goetzamann and Jorion (1999) related this to their study of emerging markets where they found a standard deviation of 34.8% compared to 19.8% in the developed markets, although the average dollar returns were higher in the emerging market (9.1%) compared with the developed market (6.9%).

Table 6.1 Beta in the basic materials indices of the African market

Market index	β_{iM} (CAPM)	β_{iM} (3-factor model)	β_{iM} (4-factor model)	β_{iM} (4-factor model + liquidity)	β_{iM} (4-factor model + liquidity and contagion)	β_{iM} (4-factor model + liquidity, contagion and higher moments)
South Africa	1.05411*** (0.119640)	0.814259 *** (0.0819126)	0.810441*** (0.0798892)	0.782204*** (0.0833705)	0.771684*** (0.0805736)	0.771138*** (0.0791532)
Emerging Africa	0.788427*** (0.0677367)	0.803047*** (0.0644096)	0.797338*** (0.0628137)	0.790198*** (0.0654904)	0.775882*** (0.0629981)	0.766978*** (0.0645285)
Emerging Africa excluding South Africa	0.773389*** (0.0380698)	0.763495*** (0.0373764)	0.570914*** (0.0463033)	0.577538*** (0.0457881)	0.570192*** (0.0458402)	0.563816*** (0.0457841)
Frontier Africa	0.198098*** (0.0624902)	0.209767*** (0.0623929)	0.205892*** (0.0645382)	0.217368*** (0.0614017)	0.183974*** (0.0560353)	0.188206*** (0.0567163)

This Table highlights the beta for the CAPM, the 3-factor model, the 4-factor model, the 4-factor model with liquidity, the 4-factor model with liquidity and contagion and the 4-factor model with liquidity, contagion and higher moments.

However, beta within the Fama and French three-factor model was 0.814 but was also significant at the 1% level, indicating that the basic materials index in the South African market is less risky than the market index, within a multifactor model. Market beta is lower than 1 due to the interaction between beta, size and book-to-markets value. This is also seen in Fama and French (1996). Within the four-factor model, beta was 0.810 and significant at the 1% level, indicating the impact of the interaction between the variables. For the liquidity-augmented model and the higher-moment augmented model (including the models that account for the contagion effect), beta remained positive and significant at the 1% level, with a beta value of between 0.771 and 0.782.

As shown on Table 6.1, beta for the emerging African market were all positive and significant at the 1% level, with values between 0.767 and 0.803. This demonstrates that the basic materials index in the emerging African market is less risky compared with the market index. Within the emerging African market excluding the South African market, beta was also positive and significant, with values between 0.564 and 0.779. I do, however, notice a decrease in the beta when the model accounts for the momentum factor, from about 0.77 to about 0.57, indicating that a greater part of the variation in returns is explained by the momentum factor in this market.

Beta within the frontier African market is far lower than those in the rest of the sample, with values between 0.184 and 0.217, which were all positive and statistically significant at the 1% level. This is perhaps the opposite of what is expected, as I would normally expect the frontier market to have a higher beta than the emerging and South African market, given how segmented they are from world markets. This phenomenon is related to the applicability of these models to this market and suggests that the CAPM and multifactor models may not be entirely appropriate within the frontier African markets, especially with adjusted R^2 being quite low when compared with the rest of the sample.

The predictive power of beta as identified in this study has been widely reported in the literature, as seen in Kothari, Shanken and Sloan (1995) and Carhart (1997), and the evidence in this study suggests beta is priced in the African equity markets**.** But there are clear variations in the value of beta across the markets, as I observe a decreasing beta across all models as I go from the more integrated market of South Africa to the more segmented markets in the frontier market index. This demonstrates that the riskiness (relative risk) of the basic materials indices diminishes with the degree of segmentation of the African market with world markets.

The rationale behind this phenomenon results from the use of a domestic market index and the basic materials indices within each market. This is because the more the market is segmented, the more the basic materials index in the countries (for each index) will become a larger part of the whole market, and hence will potentially become less risky than the market index. This is particularly the case in the African market due to the export-commodity nature of many African countries, as noted in Assefa and Mollick (2014). This decreasing beta value for countries less integrated to world markets is also reported in Hearn, Piesse and Strange (2010).

Further evidence is provided by Harvey (1995a) identify only seven emerging markets to have betas significantly higher than zero in their sample of 20 emerging markets over the period from 1979 to 1992. Harvey (1995b) concludes that beta does not accurately measure risk in emerging markets. Collins and Abrahamson (2006) provide evidence against the accuracy of beta in the African market.

6.9 The size effect

The importance of size in asset pricing has been identified in Banz (1981), Reinganum (1981) and Fama and French (1993). This was also observed in the result of this study, with a significant negative size factor within the South African market.

Table 6.2 Factor loading for the size variable of the basic materials indices in the African market

Market index	3-factor model	4-factor model	4-factor model + liquidity	4-factor model + liquidity and contagion	4-factor model + liquidity, contagion and higher moments
South Africa	−0.606609 *** (0.0731787)	−0.603633*** (0.0712710)	−0.413264*** (0.0769728)	−0.418064*** (0.0763046)	−0.418051*** (0.0758411)
Emerging Africa	0.0763167* (0.0417691)	0.0706369* (0.0425021)	0.0911008** (0.0439646)	0.0913560** (0.0428271)	0.0959405** (0.0428184)
Emerging Africa excluding South Africa	−0.175687*** (0.0491774)	−0.212918*** (0.0480996)	−0.215075*** (0.0466551)	−0.209831*** (0.0457877)	−0.203346*** (0.0446733)
Frontier Africa	0.0337210 (0.0207665)	0.0382279* (0.0201338)	0.0418047** (0.0207288)	0.0444451** (0.0196571)	0.0440862** (0.0186608)

The size discount is significant at the 1% for all models within the South African market. Within the emerging African market, the size variable is positive and significant at the 5% level across all models besides the three- and four-factor models where the size factor is significant at the 10% level. In the emerging African market excluding South Africa, the size variables are negative and statistically significant at the 1% level within all models, while within the frontier African market, evidence of the size effect is mixed, with the size factor in most models being positive and significant at the 5% or 10% level, while being insignificant within the Fama-French three-factor model.

The evidence in the South African market and emerging African market excluding South Africa is consistent with the findings in Hearn et al. (2010), who find negative values of the mean of SMB, which indicates a reverse size effect from that in Fama and French (1993). They also imply that this is due to the extremely heterogeneous feature of the universe of stocks where there are considerable differences between firms in the developed markets and those in the emerging markets. The results show that the return on the large-cap portfolio is higher than the returns on the small-cap portfolio within the South African market and the emerging African market excluding South Africa. Hou, Xue and Zhang (2015) also agree and state that anomalies in microcaps are unlikely to be exploited in practice due to transaction costs and lack of liquidity in these markets. Hearn and Piesse (2009) found similar results in their study of the north African market, while Martinez et al. (2005) reports the reversal of the documented size effect.

Van Dijk (2011) highlighted the development of theories on the risk-based explanation of the size effect in which the size effect arises endogenously as a result of systematic risk. This corresponds to the evidence within the emerging African market and the frontier African market in this study, which found a size premium. As in Banz (1981), Lamoureux and Sanger (1989) and Barry et al. (2002), I find that small-cap firms outperform large-cap firms in the emerging African market and the frontier African market. However, size seems to be significant in the frontier African market only when momentum is accounted for. Clearly the evidence provided demonstrates that the importance and direction of the size effect depends on the market surveyed.

6.10 The value effect

Asness, Moskowitz and Pedersen (2013) identify the importance of the value factor in asset pricing. They follow the work of Fama and French (1992), who find that size and value are the only priced variables in asset pricing. Fama and French (1992) highlight that stocks with a high book-to-market ratio have reliably higher returns than low book-to-market stocks. The book-to-market factor in the South African market was positive but insignificant across all models, indicating that there is no value premium in the South African market. The book-to-market factor within the emerging African market was negative but also insignificant across all models, also indicating that the value factor is also not priced in the emerging African market.

There is considerable consensus that the value factor is not important in asset pricing. This is consistent with the findings in Kothari et al. (1995), which suggest that the value premium is due to data-snooping; they also highlight that the value premium may be due to survivorship bias. However, this data is survivorship bias-free. The recent research by Fama and French (2015) also indicates that the value factor is dead.

Table 6.3 Factor loading for the value variable of the basic materials indices in the African market

Market index	3-factor model	4-factor model	4-factor model + liquidity	4-factor model + liquidity and contagion	4-factor model + liquidity, contagion and higher moments
South Africa	0.0525296 (0.0834949)	0.0283707 (0.0779701)	0.0180821 (0.0739083)	0.0295652 (0.0729561)	0.0300583 (0.0730565)
Emerging Africa	−0.0803463 (0.0611953)	−0.0574970 (0.0621561)	−0.0626380 (0.0622812)	−0.0758104 (0.0631049)	−0.0835243 (0.061927)
Emerging Africa excluding South Africa	0.0873957* (0.0446112)	0.0836887** (0.0395328)	0.0742680* (0.0391656)	0.0712296* (0.0380578)	0.0676494* (0.037291)
Frontier Africa	0.0234962 (0.0266539)	0.0450782* (0.0265515)	0.0483362** (0.0259348)	0.0445542* (0.0252050)	0.0481174* (0.025701)

However, the book-to-market factor in the emerging African market excluding South Africa is positive and significant at 10% for all models apart from the Carhart 4-factor model, where the value factor is significant at the 5% level. This significant value factor is due to the structure of the index and the interaction of the value factor with other factors in the model. This is similar to some findings in the literature, as in Fama and French (1998), Barry et al. (2002) and Drew and Veererghavan (2002).

In investigating the frontier African market, this study finds that the book-to-market value factor is insignificant within the Fama-French 3-factor model, but significant at 5% or 10% levels within the Carhart 4-factor models and its augmented variants; hence the importance of the value factor within the frontier African market is rather inconsistent. This concern is also highlighted in Loughran (1997), who insists that there is no consistent relationship between book-to-market value and realised returns. Bundoo (2008) argues that there is a lack of convincing empirical evidence that the value premium is present in emerging equity markets generally, and particularly in the African markets. The results seem to demonstrate that the value factor becomes significant only when the momentum factor is accounted for.

6.11 The momentum effect

Carhart (1997) identified the importance of momentum in asset pricing by augmenting the Fama-French three-factor model by Jegadeesh and Titman (1993). According to Novy-Marx (2012), momentum trading refers to buying past winners and selling past losers. Evidences have been provided by numerous researchers on the profitability of momentum trading strategies, e.g. Griffin et al. (2003), Jegadeesh and Titman, (1993, 2001), Jagadeesh (1990), Chui et al. (2003), Rouwenhorst (1998, 1999) and De Bondt and Thaler (1985), but there remains to be seen a consensus on the source of these profits. Badrinath and Wahal (2002) highlight the implication of momentum trading for the efficient markets by stating that it destabilises stock prices, which contrasts with Friedman's (1953) argument, which insists that rational speculation must stabilise asset prices.

The momentum factor within the South African market and the emerging African market was positive but insignificant across all models. This is in line with the findings in Rouwenhorst (1999), who argues that it is quite difficult to detect momentum in emerging markets. He highlights that given the high trading costs, the existing evidence does not support the presence of momentum returns in emerging markets. Conrad and Kaul (1998) and Bulkey and Nawosah

(2009) insist that momentum is mainly explained by risk while Lo and Mackinley (1990) suggest that the sources of momentum returns are positive serial correlation (negative cross-sectional correlation) and dispersion in unconditional mean returns. Bartens and Hassan (2010) find that the relationship between momentum and realised returns is unstable, suggesting that this may be due to time variation, related to changes in economic states. In their study of overreaction effect in the UK, Andrikopoulos et al. (2011) also found evidence of time variation.

Table 6.4 Factor loading for the momentum variable of the basic materials indices in the African market

Market index	4-factor model	4-factor model + liquidity	4-factor model + liquidity and contagion	4-factor model + liquidity, contagion and higher moments
South Africa	0.0407704 (0.0505914)	0.0416657 (0.0479756)	0.0360936 (0.0466760)	0.0358491 (0.0468751)
Emerging Africa	0.0359296 (0.0343935)	0.0341063 (0.0338087)	0.0306662 (0.0333789)	0.0287265 (0.0329108)
Emerging Africa excluding South Africa	0.197877*** (0.0315364)	0.202097*** (0.0300815)	0.201803*** (0.0300931)	0.198446*** (0.0292625)
Frontier Africa	0.0456719** (0.0193136)	0.0418725*** (0.0189410)	0.0408926** (0.0181898)	0.0406959** (0.017666)

The momentum factor is, however, positive and significant at the 1% level for all models that include the momentum factor within the emerging African market excluding South Africa. The momentum factor is also positive and significant at the 5% level for all models that include the momentum factor within the frontier African market. This is consistent with the findings in Carhart (1997) and Jegadeesh and Titiman (1993), who find that the profitability of momentum strategies is not due to their systematic risk or to delayed stock-price reaction to common factors. This is also consistent with the findings in Chui et al. (2000) and Griffin, Ji and Martin (2003).

The difference between the importance of momentum in the South African market/emerging African market versus the emerging African market excluding South Africa/frontier African market demonstrates the impact of the degree of segmentation of the two markets on the importance of momentum, as highlighted in Assefa and Mollick (2014).

6.11.1 Behavioural explanation of momentum

Given the presence of momentum profit in the emerging and frontier African markets and the persistence of momentum profits reported in the literature, it is important to understand its cause. According to Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1998) highlight that momentum profits are due to inherent bias in the way that investors interpret information. They believe that the holding period returns arise because of a delayed overreaction to information that pushes prices of winners above their long-term values and losers below their long-term values. The behavioural hypothesis implies that the return on losers should exceed the returns on winners in the subsequent holding period. Jegadeesh and Titman (1999) find evidence in support of the behavioural explanation of momentum, as does Rouwenhorst (1998) who finds out-of-sample evidence of momentum effect in many European countries.

Negative autocorrelation in returns over a three to five year horizon (long-term reversal) is documented in De Bondt and Thaler (1987) and in Chopra et al. (1992); however, the economic rationale remains unclear. Copper (1999) continues to assert that overreaction is the cause, although Gutierrez and Kelley (2006) believe that this may have been caused by illiquidity-related price reversals. Haugen and Baker (1996) find no evidence that systematic risk or other measures of risk are important for the cross-section of equity returns. An in-depth review of momentum literature is detailed in Subrahmanyam (2007).

However, according to Conrad and Kaul (1998), the profitability of momentum strategies is simply compensation for risk. Following from this, Lo and MacKinlay (1990) assert that momentum strategies should yield positive average returns, where stocks with high (low) unconditional expected returns in adjacent periods are expected to have high (low) realised returns in both periods. This contradicts the expectation within behavioural finance. Within our study, I do not find evidence of a behavioural anomaly as our results are consistent with the risk-based explanation of momentum, as highlighted in Lo and MacKinlay (1990). The factor loadings on the momentum variables in all markets are all positive, although only significant within the emerging African market excluding South Africa and the frontier African market. Hence I can conclude that the momentum profit identified is not a result of behavioural biases.

6.12 The liquidity effect

Research into the importance of liquidity in asset pricing has picked up steam in recent years since the study by Aminud and Mendelson (1986). Brennan and Subrahmanyam (1996) and Liu (2006) find a return-illiquidity relation even after taking price, size and book-to-market factors into account. In this study, I find that liquidity is priced at the 1% significance level within all liquidity-augmented models in the South African market. However, the liquidity factor is negative, indicating that returns decrease when the illiquidity premium increases. This contrasts with the findings in Amihud and Mendelson (1986), Pástor and Stambaugh (2003) and Chordia et al. (2000). However, Amihud (2002) finds a significant negative return-liquidity relation even in the presence of beta, size and momentum.

The liquidity factor is also significant at the 5% level within the emerging African market excluding South Africa, but unlike the models within the South African market, liquidity factors for the emerging market excluding South Africa are positive, which is consistent with theoretical assumptions. Assefa and Mollick (2014) identify that stock returns are positively related to liquidity in the African stock markets when South Africa is excluded from the sample of countries. This, they say, may reflect some of the microstructure model mechanisms captured in Amihud and Mendelson (1986), Vayanos (1998), and Baker et al. (2002). These microstructure models infer that increases in liquidity predict lower subsequent returns.

This positive link has also been reported in Gervais et al. (2001) and Jun et al. (2003). Others who found liquidity to be priced include Pástor and Stambaugh (2003), Martinez et al. (2005) and Liu (2006).

Table 6.5 Factor loading for the liquidity variable of the basic materials indices in the African market

Market index	4-factor model + liquidity	4-factor model + liquidity and contagion	4-factor model + liquidity, contagion and higher moments
South Africa	−0.318495*** (0.0859401)	−0.324881*** (0.0842805)	−0.324839*** (0.0841023)
Emerging Africa	−0.0351032 (0.0436339)	−0.0407794 (0.0423631)	−0.0427367 (0.0424116)
Emerging Africa excluding South Africa	0.0682631** (0.0314736)	0.0723881** (0.0315716)	0.0709348** (0.0318461)
Frontier Africa	−0.0374348 (0.0317782)	−0.0419267 (0.0300360)	−0.0399902 (0.0304431)

The rationale behind the illiquidity factor in the African market is that liquidity can be seen as the cost of immediate execution and the willingness of an investor to transact at a favourable price, which will create a trade-off problem. The investor may either insist and execute a transaction immediately at a current bid or ask price, or wait to transact at a favourable price. In the African market, this execution cost is usually high due to the larger bid/ask spread. The execution cost (transaction cost) will thus become a cash outflow that will reduce future returns. Lischewski and Voronkova (2012) identify similar results. Another problem related to illiquidity in African markets is the problem of adverse selection, which according to Brennan and Subrahmanyam (1996) arises from the activities of informed traders. Lischewski and Voronkova (2012) highlight that a marginal investor may demand for higher rates due to the severity of the adverse selection problem if they are uninformed.

The liquidity variables are not significant within the models in the emerging African market and the frontier African market, indicating that liquidity is not a priced variable within these markets. This is rather unexpected as the problems of illiquidity and thin trading have been widely researched as acknowledged in literature; see Dimson (1979), Cohen et al. (1983) Lo and MacKinlay (1990), Miller et al. (1994) and Bowie (1994). However, Lischewski and Voronkova (2012) identified the conflicting results produced by various studies that examined the relevance of liquidity in asset pricing. Jun et al. (2003) point out the lack of integration of emerging African markets with the global economy and highlight that the lack of liquidity will not function as a risk factor, thus cross-sectional returns will not necessarily be lower for liquid markets. The insignificance of the liquidity factor within the emerging African market may be due to the characteristics of the surveyed markets, i.e. the interaction between the South African, Egyptian and Moroccan markets. This is because the results show that the liquidity factor within the South African market is negative and significant but positive and significant within the emerging African market excluding South Africa, hence a combination of the two markets has led to an insignificant liquidity factor. This evidence has also been found in Hearn (2011), who admits that the effect of liquidity on asset pricing depends on the structure of the surveyed stock market.

However, given that logical investors will prefer to invest in liquid assets, Lesmond (2005) highlights that the illiquidity of emerging market stocks relative to the more developed market will present problems. Bekaert et al. (2003) insist that models that account for liquidity risk outperform other models that incorporate only a market risk factor in predicting future returns and this is observed in this study as seen in Sections 6.5 and 6.6 above.

6.13 Higher-order moment effect

Jean (1971) and Scott and Horvath (1980) argue that the higher moments of returns distribution are very important beyond the mean-variance context established by the CAPM. This also follows the findings in Kraus and Litzenberger (1976), who expanded the utility function beyond the second moment to examine the importance of skewness. Unlike the Sharpe-Lintner (standard) CAPM, which implies that investors are only compensated for bearing the systematic covariance risk, Fang and Lai (1997) found that investors are compensated for bearing the systematic cokurtosis risk, as well as the systematic covariance and coskewness risks, with higher expected returns. However, the importance of coskewness and cokurtosis risk measures (third and fourth moments of return distribution) in supplementing the covariance risk in asset pricing remains debatable.

Table 6.6 Factor loading for the coskewness factor of the basic materials indices in the African market

Market index	4-factor model + liquidity, contagion and higher moments
South Africa	−0.000379482 (0.00110353)
Emerging Africa	−0.000274863 (0.00057182)
Emerging Africa excluding South Africa	0.000808879 (0.00356724)
Frontier Africa	0.00406455** (0.00187213)

Table 6.7 Factor loading for the cokurtosis factor of the basic materials indices in the African market

Market index	4-factor model + liquidity, contagion and higher moments
South Africa	−0.0084403 (0.0844355)
Emerging Africa	0.193561** (0.0870456)
Emerging Africa excluding South Africa	0.370089** (0.168695)
Frontier Africa	0.0321275 (0.131951)

Within the South African market, I find that coskewness and cokurtosis are both not significant within a liquidity- and higher-moment augmented four-factor model, when contagion is accounted for**.** This suggests that the higher-order moments are not important in explaining ex-ante returns in the South African basic materials sector. As noted earlier, this is consistent with the findings in Singleton and Wingender (1986), who observe that higher moments of return distribution do not persist through time. DeMiguel and Nogales (2007) and Hung (2008) highlight that the poor explanatory power of the higher moments result from parameter uncertainty. This, however, may not be the case as the analysis had adjusted the model for some time-varying problems. Other researchers who investigated the effect of skewness and kurtosis include Faff and Chan (1998), Adock and Shutes (2005), Jurczenko et al. (2005) and Polimenis (2002).

However, within the emerging African market and the emerging African market excluding South Africa, the cokortosis measure is important at the 5% levels, respectively, but the coskewness measures are both insignificant. This is consistent with findings in Friend and Westfield (1980) and Hung (2008), who find no premium for skewness but indicate that kurtosis offers some explanation of realised returns. This also highlights the fact that returns in these markets are leptokurtic and supports the findings in Hwang and Satchell (1999), who identify the explanatory power of higher moments in emerging markets. The insignificance of the skewness factor may be due to the collinearity between the risk measures or the failure of unconditional models as highlighted in Pettengill et al. (1995).

The coskewness measure is significant within the frontier African market while the cokurtosis measure is insignificant. This highlights the importance of skewness within the frontier African market and identifies that returns increase with an increase in the right-side skewness measure. With a large positive skewness (high probability of a large positive return), investors may be willing to hold portfolios even when expected returns are negative, as also identified in Harvey and Siddique (2000). Chang, Christoffersen and Jacobs (2013) do, however, provide some evidence of time variation in higher moments. Hence I cannot rule out the impact of time variation on the behaviour of the higher-moment factors in our study.

6.14 Contagion effect in the African market

One of the commonly made assumptions of the static CAPM is that the betas of assets remain constant over time, which is quite unrealistic given that the business cycle will present variations to a firm's cash flow and also the degree of a firm's financial leverage, hence a varying relative risk, as highlighted in Jagannathan and Wang (1996). This implies that in theory, the CAPM could hold conditionally on time information, period by period, even when the unconditional CAPM does not hold. This would also account for the presence of structural break/regime shift in volatility that may result from exogenous events. Structural breaks in the surveyed markets are analysed in Section 3.8.4 of Chapter 3.

This study includes a dummy variable for contagion, representing the financial crisis and the Arab Spring, within the models. The dummy variable is significant in all four samples within the liquidity-augmented four-factor model. But when higher moments are included in the models, the contagion variable within the emerging African market and the emerging African market excluding South Africa became insignificant, while remaining significant in the South African market and the frontier African market. This identifies some contagion effects on the estimates of the models, calling into question the stability of beta as theorised in the Sharpe-Lintner CAPM. Many authors believe that the beta is indeed unstable. In his seminal article, Blume (1971) highlighted the tendency of beta to mean-revert. In the US, Fabozzi and Francis (1978) identified that most US equities have time-varying betas. If the existing literature mostly focuses on the developed market becsause of the problems raised by beta instability, there should be even more interest in emerging markets as the effects are more likely to be more significant, and even more so in the African markets. However, research on beta instability in the African market continues to be very thin.

I, however, observe the impact of higher moments on the contagion factor within the emerging African market and the emerging African market excluding South Africa. This is likely due to the interaction between the higher moments and the contagion variable. Time variation will be more of a problem as most African countries are segmented, to varying degrees, from world markets. A good example of the effect of segmentation can be seen in the results within this study, as South Africa is significantly different from Egypt and Morocco due to its higher level of integration with world markets. This has huge implications for the emerging market index because the behaviour of returns changes with the degree of integration. Hence, as stated in Bekaert and Harvey (2002), prices should rise and expected returns should decrease as markets transition from a segmented to an integrated market.

According to Bekaert et al. (2011), segmentation within the US is quite small (with a mean of 1.5%) and fairly constant (with a time-series standard deviation of 0.6%). This is relative to the level of measured segmentation of developed countries, with a mean of 3.0% and average time-series standard deviation of 1.7%. On the other hand, emerging market economies had a high measured segmentation, with a mean of 5.0% and an average time-series standard deviation of 3.1%. According to Harvey (1995), it has always been argued that emerging markets are segmented from world capital markets because returns are more likely to be influenced by local rather than global information variables.

Other determinants of market segmentation, as identified in Bekaert et al. (2011), include measures of de facto openness, political risk and institutions, financial development, risk appetite and business cycle, informational friction and growth determinants. When these factors are considered, many observers admit that South Africa is more integrated with world markets than any other African country. This is supported by Agyei-Ampomah (2011), who remarks that stock markets in Africa, with the exception of South Africa, are still segmented from global markets despite their liberalisation efforts. Hence the effect of varying information will be investigated in a conditional CAPM-type analysis.

6.15 Differences between the emerging and frontier African markets

The study shows some important differences between the emerging and the frontier African markets, with the most important being arguably the model that performs best within each market. I find that the liquidity- and contagion-augmented four-factor model performs best in the emerging African market, while the liquidity-, higher-moment and contagion-augmented four-factor model performs best in the frontier African market. The adjusted R^2 in the frontier African market was found to be very low compared with the adjusted R^2 in the emerging African market. Another major difference relates to the absence of the value premium in the emerging African market, while being priced in the frontier African market. This conforms to the findings in the literature that suggest that the value factor becomes unimportant with time.

The momentum factor was found to be absent within the emerging African market, but was important in the frontier African market. This is attributable to delayed stock-price reaction to common factors, which diminishes as the market becomes more efficient. Our study show that momentum becomes unimportant as a country moves from being a frontier market to being an emerging market in the African continent. Another key difference is in the higher moments that are priced in each market. I find that cokurtosis is priced in the emerging African market while coskewness is priced in the frontier African market. Also, contagion seems to affect the frontier African market consistently, but within the emerging African market the contagion effect disappears when higher moments are accounted for.

6.16 Chapter conclusion

The threefold aim of this chapter was to highlight the best performing model in each market, to evaluate the importance of each variable in these markets and to evaluate the impact of contagion. I find that the liquidity-augmented four-factor model, which accounts for the contagion effect, performs best in the South African market, the emerging African market and the emerging African market excluding South Africa, while the higher-moment and liquidity-augmented four-factor model, which accounts for the contagion effect, performs best in the frontier African market.

In analysing the variables in the models, this study finds beta to be consistently important across all models and all markets. Size was found to be negative and significant in the South African market and the emerging African market excluding South Africa, indicating that stocks of big firms outperform those of small firms. It was also significant in the emerging African market and the frontier African market, but with a positive coefficient, indicating a premium for holding stocks of small firms.

The book-to-market value factor was consistently insignificant across all models within the South African market and the emerging African market. This corresponds to the recent finding in Fama and French (2015). However, the book-to-market value factor within the emerging African market excluding South Africa is positive and significant across all models, highlighting the value premium within the market. This also demonstrates the impact of the exclusion of the South African market from the emerging Africa market on the characteristics of the index. The significance of the book-to-market value factor was found to be inconsistent within the frontier African market.

The momentum factor was unimportant in the South African market and the emerging African market, but was found to be positive and significant within the emerging African market excluding South Africa and the frontier African market. The liquidity factor was significant within the South African market, but with a negative coefficient. This indicates that there is no reward for holding illiquid stock, but rather a reward to picking liquid stocks. The liquidity factor was found to be positive and significant within the emerging African market excluding South Africa, indicating an illiquidity premium in this market. Surprisingly, liquidity was found to be unimportant within the emerging African market and the frontier African market, hence I conclude that the effect of liquidity on asset pricing depends on the structure of the surveyed stock market

I find coskewness and cokurtosis to be insignificant within the South African market, indicating that higher moments are not priced in this market. The cokurtosis factor was significant within the emerging African market and the emerging African market excluding South Africa, but the coskewness measure was insignificant in these markets. This is similar to the findings in Hung (2008), who found no premium for skewness, but indicates that kurtosis offers some explanation of realised returns. However, I found the coskewness measure to be significant within the frontier African market while the cokurtosis measure was insignificant within the liquidity and higher-moment augmented four-factor model, when the contagion effect is accounted for.

The contagion-effect dummy was introduced within the models to investigate the possible effect of time variation within the data. The dummy variable was significant in the South African market, the emerging African market (except for the liquidity and higher-moment augmented four-factor model), the emerging African market excluding South Africa (except for the liquidity and higher-moment augmented four-factor model) and the frontier African market. This provides some evidence of time variation.

The findings do, however, indicate that the importance and impact of the variables studied depend on the structure of the market surveyed, as also found in Andrikopoulos et al. (2008).

Given the significance of the contagion dummy in most of the models, the next chapter will examine the impact of time variation on the estimates of beta using a multivariate GARCH-based approach.

7 CONDITIONAL CAPM

7.1 Introduction and structure of chapter

A further issue of robustness concerns the parameter stability of the basic (unconditional) CAPM factors, of beta, size, book-to-market value, momentum, liquidity and the higher moments. The results between January 2004 and January 2015 largely assume that the factor loading parameters are constant. This may be too far an assumption in the African market, as I have seen frequent policy and regulatory changes within the sample period. These changes would have affected the perspective of investors, especially the institutional investors, and could have caused structural breaks (regime shifts) in the returns-generating and/or volatility clustering.

Also, as highlighted in the literature review (Chapter 2), many researchers question the assumption of a constant (stable) returns-beta relationship due to the possible presence of structural breaks resulting from market liberalisation, institutional changes and drastic political and economic policy changes. These are even more so in the African equity markets due to the relative newness of the market. Given the time period in view, considerable shifts in regimes are to be expected.

In Chapter 3, Section 3.8.4.2, I establish the presence of breaks that can potentially affect the returns-generating process with the South African market index, the emerging market index, the emerging market less South African market index and the frontier market index. Given the prevalence of the structural changes identified, I have attempted to control for this within the unconditional asset-pricing models in Chapters 5 using a dummy variable for the effect of financial and political contagion on the sample. As discussed in Chapter 6, Section 6.14, the contagion dummy was mostly significant across the sample, indicating a possible exogenous influence on the return-generating process.

This demonstrates the possibility for beta to increase significantly during crisis periods. As seen in Jagannathan and Wang (1996), there is a growing acknowledgement that beta and expected return will in general depend on the nature of the information available at any given point in time and vary over time. Some of the points that present a problem to the static (unconditional) CAPM include the rise in the beta of equities during a recession caused by leverage, the varying effect of the business cycle on different types of assets, effects of technological changes and changes in consumer taste. Following the most recent financial crisis (2007/2008), which started in the US, and the Arab Spring in some MENA countries, there may be some time-varying impact on beta in African countries. This impact is expected via contagion from the affected areas.

In the next sections, I use the more robust time-varying models to test for stability in beta. I use contagion from the financial crisis and the Arab Spring for this test because as stated in King and Wadhwani (1990), price changes in one market are expected to reflect on the markets by means of structural contagion coefficients. They also identified that this is more likely during periods of market crash.

7.2 Time-varying correlation and beta analysis

I adopt the DCC-MGARCH type model as the time-varying methodology for this section. To ensure that the optimal model is employed I also use the DCC GJR-GARCH model (and also the ADCC to allow for the possibility of asymmetry), allowing the impact of lagged squared returns on the current conditional variance to change according to the sign of the past returns.

I estimate the conditional correlations at each point in time, which is unlike the static model. This is done by estimating conditional variance terms and conditional covariance, which are estimated from $Q_t = [\mathrm{q}_{\mathrm{ij,t}}]$, with Q_t, being the covariance matrix.

To estimate the conditional correlation, the conditional variance and conditional covariance needs to be estimated at each point in time.[165]

$$\rho_{\mathrm{ij,t}} = \frac{\text{Conditional covariance}_{\mathrm{ij,t}}}{\sqrt{\text{conditional variance}_{\mathrm{it}}\text{conditional variance}_{\mathrm{jt}}}} = \frac{\mathrm{q}_{\mathrm{ij,t}}}{\sqrt{\mathrm{q}_{\mathrm{ii,t}}\mathrm{q}_{\mathrm{jj,t}}}} \quad (7.1)$$

The conditional beta is also estimated at each point in time as follows

$$\beta_{\mathrm{ij,t}} = \frac{\text{Conditional covariance}_{\mathrm{ij,t}}}{\text{conditional variance}_{\mathrm{jt}}} = \frac{\mathrm{q}_{\mathrm{ij,t}}}{\mathrm{q}_{\mathrm{jj,t}}} \quad (7.2)$$

$where\ i =$ the asset portfolio and $j =$ the market portfolio

[165] The variance and covariance structures are shown in the chapter appendix

7.2.1 Multivariate DCC model in estimating conditional correlations

The model applied follows from Engle (2002) and uses a variant of the original DCC multivariate GARCH model.

The use of a system of equations or a series of equation pairs is the usual way of applying this methodology, where the equation pairs are the asset portfolio and the market portfolio, for each sample. I run the model on the basis of four equation pairs, for the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market. I exclude the contagion dummy variable (for the 2008 financial crisis and the Arab Spring) and this will be used for further tests later in the chapter.

The first step is to estimate the residual returns mean equations in a pairs-based modelling procedure. These models will include innovations of size, book-to-market value, momentum, liquidity, skewness and kurtosis (the mean equation form is discussed below) and are as follows:[166]

$$r_{it} = \alpha_i + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{im}UMD_t + \beta_{ip}IMV_t + \beta_{ie}S_t + \beta_{ik}K_t + \varepsilon_{it} \quad (7.3)$$

$$r_{jt} = \alpha_j + \beta_{js}SMB_t + \beta_{jh}HML_t + \beta_{jm}UMD_t + \beta_{jp}IMV_t + \beta_{je}S_t + \beta_{jk}K_t + \varepsilon_{jt} \quad (7.4)$$

where i represents the asset portfolio and j represents the market portfolio. r_{it} is the return on the asset portfolio less the risk-free rate, while r_{jt} is the return on the market portfolio less the risk-free rate. β_{is}, β_{ih}, β_{im}, β_{ip}, β_{isk} and $\beta_{ik}$are factor loadings on the size, book-to-market value, momentum, liquidity, skewness and kurtosis factors, respectively. $\beta_{js}, \beta_{jh}, \beta_{jm}, \beta_{jp}, \beta_{jsk}$ and β_{jk} are factor loadings for the variables in respect of the market *J*.

The methodology assumes that residuals are conditionally multivariate student distribution as the t-distribution generates the lowest forcaset errors compared to the

[166] Proof for the correct identification of time-varying beta is in chapter appendix 1

normal error distribution and the generalized error distribution, as seen in Marshall, Maulana and Tang (2009).

The variance equations are hence derived from the residuals from the mean equation pairs. Following the peculiar characteristics of the African continent and to find the best structure, I start off with the *GARCH (1, 1)* format (discussed below). They are as follows:

$$\delta_{it}^2 = \alpha_{i0} + \alpha_{i1}\,\varepsilon_{it-1}^2 + \beta_{i1}\delta_{it-1}^2 \qquad (7.5)$$

$$\delta_{jt}^2 = \alpha_{j0} + \alpha_{j1}\,\varepsilon_{jt-1}^2 + \beta_{j1}\delta_{jt-1}^2 \qquad (7.6)$$

where the conditional variance is represented by δ_t^2, the intercept is denoted as α_0, the residuals are denoted as ε and the ARCH and GARCH parameters are denoted α_1 and β_1, respectively.

The second form used is the GARCH *(2, 1)*, with the format as follows:

$$\delta_{it}^2 = \alpha_{i0} + \alpha_{i1}\,\varepsilon_{it-1}^2 + \beta_{i1}\delta_{it-1}^2 + \beta_{i2}\delta_{it-2}^2 \qquad (7.7)$$

$$\delta_{jt}^2 = \alpha_{j0} + \alpha_{j1}\,\varepsilon_{jt-1}^2 + \beta_{j1}\delta_{jt-1}^2 + \beta_{j2}\delta_{jt-2}^2 \qquad (7.8)$$

I also use the GJR-GARCH (Glosten, Jagannathan and Runkle, 1993). This allows the conditional variance to respond differently to the past negative and positive innovations.

$$\delta_t^2 = \omega + \sum_{i=1}^{p}\alpha_i {\varepsilon_t}^2 + \sum_{j=1}^{q}\beta_j\,{\delta^2}_{t-j} + \sum_{i=1}^{p}\gamma_i I_{t-1}{\varepsilon^2}_{t-i}. \quad (7.9)$$

$$I_{t-1} = \begin{cases} 1\ if\ \varepsilon_{t-1} < 0 \\ 0\ if\ \varepsilon_{t-1} \geq 0 \end{cases}$$

The conditional correlations and conditional betas are estimated from the DCC equation (Equation 7.10) and the asymmetric dynamic conditional correlation (ADCC) (Equation 7.11):

$$\mathrm{Q_t} = (1 - \alpha - \beta)\overline{\mathrm{Q}} + \alpha u_{\mathrm{t-1}}u'_{\mathrm{t-1}} + \beta \mathrm{Q_{t-1}} \qquad (7.10)$$

where $Q_t = [q_{ij,t}]$, $\bar{Q} = [u_t u_t']$, the covariance matrix is represented by Q_t and the residuals standardised by their conditional standard deviation are denoted as u_t. Given the restriction for the non-negative scalars of $\alpha + \beta < 1$, the model is mean-reverting.

The ADCC follows from Cappiello, Engle and Sheppard (2006), who extended the DCC model to account for possible asymmetric issue in the time-varying conditional correlation.

$Q_t = (\bar{Q} - \alpha^2\bar{Q} - \beta^2\bar{Q} - g^2\bar{N}) + \alpha^2 u_{t-1}u_{t-1}' + g^2 z_{t-1}z_{t-1}' + \beta^2 Q_{t-1}$ (7.11), where α, β and g are scalars, $z_t = I[u_t < 0]°u_t$ (with the Hadamard product indicated by °), $\bar{N} = E[z_t z_t']$. For $\bar{Q}$ and $\bar{N}$, expectations are infeasible and replaced with sample analogues, $T^{-1}\sum_{t=1}^{T} u_t u_t'$ and $T^{-1}\sum_{t=1}^{T} z_t z_t'$, respectively.

For conditions where beta will vary considerably over time, this is will be indicated by a significant alpha coefficient value in the DCC or ADCC equation. I only report the model that performs best between DCC GARCH (1,1), DCC GARCH (2,1), DCC GJR-GARCH (1,1), DCC GJR-GARCH (2,1), ADCC GARCH (1,1), ADCC GARCH (2,1), ADCC GJR-GARCH (1,1) and ADCC GJR-GARCH (2,1) models. The superior model is based on Akaike (AIC),[167] Shibata,[168] Schwarz (SC)[169] and Hannan-Quinn (HQ)[170] information criteria.

As highlighted previously, the rationale for these forms of GARCH is the need to account for possible asymmetry. The use of lags in eliminating autocorrelation and heteroscedasticity within the model will distort the time-varying beta that I expect to measure, hence the preference for varying forms of GARCH.

Appendix Table A7.2 indicates that the alpha parameter is only significant in the frontier market. This indicates that the conditional beta changes significantly over time within the frontier market, which suggests that there is a strong likelihood that evidence of contagion could be found within the data. However, the alpha term within the South African market, the emerging African market and the emerging African market excluding South Africa is not significant. This does not necessarily eliminate the possibility of the impact of

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[167] Akaike information criterion (AIC). See Burnham and Anderson (2004)

[168] Shibata information criterion. See Shibata (1976)

[169] Schwarz criterion (SC). See Cavanaugh and Neath (1999)

[170] Hannan-Quinn criterion (HQ). See Burnham and Anderson (2004)

contagion as the parameter within these markets are quite high when compared to the frontier market. Persistence[171] within the series is estimated using the beta parameter. If $\alpha + \beta = 1$, this would in effect indicate that the series would be integrated to the order 1: i.e. I (1) as the model will not mean-revert.

The multivariate Student-t distributed errors is used to estimate the GARCH models as proposed by Bollerslev (1987).

7.3 Development of the mean equations

Table A7.1 presents results of the mean equation developed. These are single constant equations with all factors included except the market portfolio in the first mean equation and the asset portfolio in the second mean equation. The residuals to be used in estimating the conditional beta must eliminate all other factors that can influence returns. These factors are typically non-contagion-based and are used to identify contagion on the series as highlighted in Forbes and Rigobon (2002). The non-contagion factors are eliminated with the inclusion of the size, value, momentum, liquidity, coskewness and cokurtosis factors. However, autocorrelation in the residuals of either the mean or the variance equation would compromise the integrity of the methodology as identified in Tsay (2005). This will present problems for the MGARCH-DCC / MGARCH-ADCC model. Section 7.3.2 below describes the process of testing for autocorrelation.

7.3.1 Innovation of the variance equations

The variance equations developed are presented in Table A7.2, based on the most optimal GARCH form.

Given the tendency for market cycle price adjustments to be faster in the bear market phases than the pace of adjustment in the bull phases, there may be possible asymmetry in the data. To deal with this, different GARCH specifications can be considered in the markets surveyed, as identified in Section 7.2.1 above.

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[171] Persistence is measured as the half-life of shock computed as $\ln(0.5)/\ln(\alpha+\beta)$ as suggested in Engle and Sheppard (2001). The half-life is defined as the time at which a shock to correlation is expected to be halfway dissipated.

I found that the superiority of the range of alternative asymmetric GARCH models available depended on characteristics of the market being surveyed. The superior alternative within the South African market index and the emerging African market was the DCC GJR (1,1). Within the emerging African market excluding South Africa, the DCC GARCH (1,1) was superior, while the DCC GARCH (2,1) was superior in the frontier African market. The results can be seen in Appendix Tables A7.1 and A7.2. (These do not include the contagion factor, as that will be applied later-on to highlight its potential impact on the models.)

It can be noted from the tables that α_0 and β_1 were statistically significant in respect to the South African market, the emerging African market and the emerging African market excluding South Africa, with α_0 being insignificant in the frontier African market. Significance is at the 10% level. As stated in 7.2.1 above, α_1 was only significant in the frontier African market.

Attempts were made towards other GARCH models but these showed insignificant alpha in their DCC equation and the models returned lack of improvement of fit across the different alternative GARCH models.

7.3.2 Autocorrelation testing in the mean and variance equations

As highlighted earlier, the robustness of the modelling procedure will be questionable if the mean and variance equations contain autocorrelation, as also identified in Tsay (2005). Hence, a series of autocorrelation tests are performed and reported in the chapter appendix; this check for autocorrelation in the modelling process. These tests are reported in Tables A7.3 and A7.4.

The Q-statistic of Ljung and Box (1978) is employed as the autocorrelation test for the standardised residuals and standardised squared residuals on the mean and variance equations. The null hypothesis states that the parameter values are simultaneously zero; as the tests are joint tests. Rejection of the null indicates the presence of misspecification errors (i.e. autocorrelation).

The presence of ARCH effects in the variance equation is examined using the Q-statistic test on the squared standardised residuals.

7.4 Financial crisis and Arab Spring contagion

As identified in Section 3.6 of Chapter 3, the crisis period refers to the 2008 financial crisis (05/09/2008 – 29/05/2009) and the Arab Spring (14/01/2011 – 19/10/2012); hence the contagion test will be carried out for this period. This takes the form of a regression-based test of significance in respect to a regression dummy variable representing the crisis periods.

$$CB_{ij,t} = \rho_j + \gamma_j Crisis\ DUMMY_t + \varepsilon_{ij,t} \quad (7.12)$$

where $CB_{ij,t}$ is the conditional beta at time t, for the asset portfolio (*i*) relative to the market portfolio (*j*). *Crisis DUMMY$_t$* is a dummy variable taking on a value of *1* over the respective crisis periods being tested, and *0* for the non-crisis (tranquil) periods. Contagion is said to have occurred when the *Crisis DUMMY$_t$* has a positive and statistically significant parameter value. The hypothesis tested is:

$H_O : \gamma_j \leq 0$ (absence of contagion)

$H_1 : \gamma_j > 0$ (presence contagion)

A statistically significant negative parameter on the dummy variable would typically indicate a significant fall in conditional beta during the crisis period. This does not constitute contagion. The test statistic is estimated as:

$$t = \frac{\hat{\delta}_j - 0}{standard\ error(\hat{\delta}_j)} \quad (7.13)$$

7.4.1 Robustness check for contagion: the equality-of-means test

To add to the robustness of the analysis, an alternative test is also undertaken to provide some confirmation to the results identified in the first method. I use the comparison-of-means tests to examine the impact of contagion on the conditional beta, given that the conditional beta is estimated across each point in time for the sample. The test identifies the extent of the statistical significance of any differences in the mean weekly conditional beta in the non-crisis period against the mean weekly conditional beta in the crisis period (the financial crisis and the Arab Spring).

I expect the variance of the contagion period and the variance of the non-contagion period to differ, given that market volatility is usually expected to be greater during crisis periods; hence I undertake an independent sample t-test. Differing forms of the t-test can be run on the basis of (i) equal variance samples and (ii) unequal variance samples.

To determine which test to apply, I use the *Levine* test for variance equality (where the null hypothesis is variance equality). If unequal variances are identified the test becomes marginally stricter and this acts as the effective difference between the two tests.

The null hypothesis is that the mean weekly conditional beta during the financial crisis and Arab Spring is equal to the mean weekly conditional beta in the non-contagion periods. Contagion is deemed to have been found when the null is rejected.

$H_O: y2 \ \leq y1$ (absence of contagion)
$H_1: y2 > \ y1$ (presence of contagion)

where $y2$ and $y1$ are the mean weekly beta values during the crisis periods and the tranquil period respectively.

If equal variances are assumed, the pooled variance t-test may be used. This is estimated as:

$$t = \frac{y2 - y1}{s_{pool}\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim t(n_1 + n_2 - 2) \ (7.14)$$

where $s_{pool}^2 = \frac{\sum(y_{1i} - \bar{y}_1)^2 + \sum\left(y_{2j} - \bar{y}_2\right)^2}{n_1 + n_2 - 2} = \frac{(n_1 - 1)s_1^2 + \ (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$

n_1 – tranquil period sample size
n_2 – crisis period (financial crisis and Arab Spring) sample size

If unequal variances are assumed the t-test is estimated as:

$$t = \frac{y2 - y1}{s_{pool}\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim t(\ df_{satterthwaite}\ ) \ (7.15)$$

where $df_{Satterrthwaite} = \frac{(n_1 - 1)(n_2 - 1)}{(n_1 - 1)(1 - c)^2 + \ (n_2 - 1)c^2} \ and \ c = \frac{s_1^2/n_1}{s_1^2/n_1 + s_2^2/n_2}$

and s^2 is the variance. The procedure for the Satterthwaite approximation follows from Satterthwaite (1946).

7.5 Results and discussion

In this section, the graphical representation of the weekly time-varying conditional variances, conditional covariance, conditional correlation and time-varying beta within each index are shown, with the regression analysis subsequently used to identify contagion. The results of the robustness check in the form of a comparison-of-mean test will also be reported. This is used due to the fact that the use of means often obscure the considerable spikes in conditional correlation and beta over time.

7.5.1 Graphical description of the time-varying conditional beta: a stylised fact

The discussions in this section depend on the graphical presentations in the chapter appendix for the conditional variances of the asset and market portfolios, conditional covariance, conditional correlation and conditional beta for the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market. In the chapter appendix, Figures A7.1 to A7.5 relate to the South African market, A7.6 to A7.10 relate to the emerging African market, A7.11 to A7.15 relate to the emerging African market excluding South Africa and A7.16 to A7.20 relate to the frontier African market. The values for the conditional correlation and conditional beta are derived using Equations 7.1 and 7.2 respectively.

From the conditional beta charts in the chapter appendix (and in Table 7.1 below), the resource sector of the emerging African market is riskier relative to the market index than the resource sectors in the frontier African market, with beta of *0.74* and *0.23*, respectively. Beta within the frontier market is rather unexpectedly low, as typically beta for more segmented markets tend to be higher than those in more integrated markets. This pattern is also seen using the unconditional beta as discussed in Chapter 8 and also highlighted in Piesse and Strange (2010). Beta in the emerging African market ranged from *0.28* to *1.79* (range of *1.51*), compared with a range of *-0.09* to *1.27* (*1.36*) in the frontier African market.

When South Africa is excluded from the emerging African market index, the mean conditional beta becomes *0.57* and range from *0.06* to *1.57* (*1.51*). The decrease in beta when South Africa is excluded suggests that the South African natural resource sector is risker relative to the market when compared with the rest of the emerging market countries in the sample. This is also shown in the mean conditional beta of the South African market of *0.76* which ranged from *0.27* to *1.43* (*1.16*). The charts show spikes in the beta around the 2009 financial crisis within the South African market, but there were also spikes in late 2004 and in 2005.

Spikes in the conditional beta can also be seen in the emerging African market, but this is less around the 2008 financial crisis period and more around the Arab Spring. This pattern is also observed when South Africa is excluded from the emerging African market index. This points to the potential impact of the Arab Spring on the emerging African market and the limited impact of the financial crisis. Within the frontier African market, the behaviour of beta is unique as the chart shows a trending conditional beta. However, there were spikes in the trend around the financial crisis, the Arab Spring and in late 2013/early 2014.

Also, in 2005 and 2006 conditional beta turns negative; this is quite rare and indicates that the resource sector in the frontier African market performed better when the market declined within these points in 2005 and 2006. This negative beta phenomenon is usually seen in safe-haven assets, such as gold and gold stocks, which usually see increases in value as the market decreases in value. This is perhaps expected in the frontier African market as they are mainly dominated by natural resources stocks. The trending conditional beta then becomes a result of the opening up of the markets/integration with world markets, which will enhance diversification of the market and hence an increase in beta for the natural resource sector.

The impact of the financial crisis has been mixed, as the spike in the conditional beta is less pronounced in the emerging African market and the emerging African market excluding South Africa. This was more pronounced in the South African and frontier African markets. The effects of the Arab Spring are more pronounced within the African market with considerable spikes in the emerging African, emerging African excluding South Africa and the frontier African markets, but not obvious in the South African market. This relates to a possible proximity effect of the events to the markets in the sample and the effects of integration with world markets.

In the case of South Africa, the high level of integration with world markets has minimised the impact of possible African-based events (or events close to the continent). This led to an impact of the financial crisis, which started in the US, on the South African market, but not an impact from the Arab Spring, even when the Arab Spring occurred in some countries within the continent.

The financial crisis, on the other hand has affected the emerging African market excluding South Africa index but not as much as its effect on the South African market and the frontier African markets. However, this does not seem to have any effect on the emerging African market index. This is potentially due to the offsetting impact of combining South Africa with Morocco and Egypt within one index.

The trending conditional correlation supports the trending conditional beta within the frontier African market and also shows negative values within 2005 and 2006. However, unlike the South African market, the emerging African market and the emerging African market excluding South Africa which show mean conditional correlation (and range) of *0.51 (0.25), 0.55 (0.31)* and *0.55 (0.82)*, respectively, the frontier African market shows a mean value of 0.16 *(0.46).* This is much lower and can provide some diversification advantages for investments in the resource sector of the frontier markets.

The changes seen in the conditional correlations charts are largely driven by Equation 7.1, which shows the ratio of the conditional covariance to the square root of the product of the portfolio and the market conditional variances. From the conditional covariance charts in the chapter appendix, the spike around the financial crisis is quite obvious for all indices in the sample although the magnitude differs. The charts show greater increase in covariation in the emerging and frontier African markets than in the South African and even less in the emerging African market excluding South Africa index. The charts also shows two other considerable spikes within the emerging African market excluding South Africa before the financial crisis and for the Arab Spring; however, this is observed to a lesser extent within the other indices.

Considerable increase in conditional covariance does not necessarily mean an increase in conditional correlation as this also depends on the square root of the product of the variances. The conditional variances for the asset and the market portfolios are depicted in the chapter appendix. As expected, the conditional variances for the asset portfolios are higher than those of the market portfolios. Overall, there are spikes in the financial crisis period and other relatively smaller spikes within the South African and emerging African markets.

Within the frontier African market, I observe one major spike during around the financial crisis for both the asset portfolio and the market portfolio, but with a second major spike. Within the emerging African market excluding South Africa, the conditional variances are very volatile. This reflects country-specific factors in Egypt and Morocco.

There are other comparatively smaller spikes in the conditional variances for both the asset and market portfolios; these mostly reflect some African-related factors. These factors include considerable political upheavals, drastic regulatory changes and currency risks. These smaller spikes seem to be more frequent within the emerging African market excluding South Africa and are mostly related to index/country-specific events in Egypt and Morocco.

In looking at the difference between the emerging and frontier African markets, the difference in the mean values as shown in Table 7.1 demonstrates these significant differences.

Table 7.1 Mean values of conditional variance, conditional covariance, conditional correlation and conditional beta

Variable (mean value)	South Africa	Emerging Africa	Emerging Africa ex. SA	Frontier Africa
Asset portfolio conditional variance	0.000870390	0.000551695	0.000477373	0.000331507
Market portfolio conditional variance	0.000428971	0.000329728	0.000474072	0.000202341
Conditional covariance	0.000306807	0.000235691	0.000262483	0.00003377
Conditional correlations	0.507304	0.550319	0.548502	0.157209
Conditional beta	0.762146	0.739438	0.570848	0.228433

Table 7.2 Unconditional beta using the liquidity and higher-moments augmented 4-factor model

Variable	South Africa	Emerging Africa	Emerging Africa ex SA	Frontier Africa
Unconditional beta	0.779893	0.769154	0.569373	0.210801

The most indicative of the differences is the value of the mean conditional correlation and conditional beta. These are far higher in the emerging African market when compared with the frontier market, as stated earlier. The conditional covariance is also significantly different. With regards to the conditional beta, there seems to be some reverse integration effects in play, with beta increasing from the frontier markets (which are perceived to be riskier), through the emerging African markets to the South African market (which is perceived to be less risky in comparison). This is rather surprising as the reverse is usually the case in other continents. However, the evolving characteristics of the African market make these relations possible, and the expectation is that with continued integration the characteristics of this market will fall more in line with those of developed markets.

When compared to the unconditional beta as shown in Table 7.2, the conditional beta does not have a clear pattern as to the degree of underperformance of the unconditional beta, when compared with the conditional beta. The mean conditional beta is higher in the emerging African market excluding South Africa and in the frontier market, but lower in the South African and emerging African markets.

In conclusion, it is quite obvious from the charts that there has been some contagion effects on parameters in the markets surveyed. The impact on beta, however, varies across the markets surveyed. To conclude on the impact of contagion on conditional beta, the next section will employ a dummy variable test and, for robustness, a comparison-of-means test.

7.5.2 Dummy variable test for contagion

In the section, I carry out a dummy variable-based analysis for contagion effect on the conditional beta. This takes the form of a one-tail regression-based test of significance in respect to the regression dummy variable representing the crisis periods. The structure of the test was described in Section 7.2.5. Contagion is said to have occurred when the crisis dummy variable *($DUMMY_t$)* has a positive and statistically significant parameter value. This significance is based on the one-tail test at 5% and a "No" in the last column indicates no evidence of contagion while a "Yes" indicates contagion. The results are shown in Table 7.3 below.

Table 7.3 Dummy variable test for contagion effect on the conditional beta

Index	R squared	*Constant*	*Dummy*	*t – Dummy*	Evidence of impact of contagion
South African market	0.0109678	0.752449	0.0422441	2.521	NO
Emerging African market	0.0976087	0.708114	0.136449	7.873***	YES
Emerging African market excluding South Africa	0.0145153	0.559119	0.0510935	2.905**	YES
Frontier African market	0.0401773	0.204056	0.106192	4.897***	YES

*, **and *** are significance levels at the 10%, 5% and 1% points, respectively. Contagion is defined as statistical significant at the 5% level.

Table 7.3 shows evidence of contagion in the emerging African market, the emerging African market excluding South Africa and the frontier African market, but no evidence was found in the South African market. In the observed structure of the conditional beta in the South African market as shown in Figure A7.5 in the chapter appendix, there are no spikes around the Arab Spring period, while in 2004/2005 there are some spikes not considered within the time period of the dummy. These have clouded the spikes within the financial crisis period. The implication is that within the period sampled, the conditional beta does not vary much across the period, which suggests that the unconditional beta may be a good representation of relative risk in the South African resource sector.

The spike in beta around the financial crisis can also not be seen as contagion as the South African market is more closely integrated to the Western markets, where the crisis originated, than other African markets. Hence, the spike may simply be due to “interdependence”. According to Forbes and Rigobon (2002), this refers to the strong linkage that exists between markets.

For the other markets sampled, the contagion dummy is significant and indicates that beta is definitely not static as suggested by the unconditional CAPM. Within the emerging and the frontier African market, the crisis dummy variable is significant at the 1% level, and at the 5% level for the emerging African market excluding South Africa. This demonstrates that beta increases with impact of the crisis and hence invalidates the assumption of static beta in the CAPM.

For robustness, I carry out a comparison-of-means test that also tests for any impact of the crisis on conditional beta in the sampled markets.

7.5.3 Contagion robustness check

To test for the robustness of the results in Section 7.3.2, I carry out a comparison-of-means test (Levine’s test of equality of variances) where the t-test for the presence of contagion is based on a one-tail test at 5% significance level. The structure of the test to be reported is described in Section 7.2.6. As with the dummy variable test, a “No” in the last column indicates the absence of any contagion effect while a “Yes” indicates the presence of contagion. Table 7.4 below show the results of the test.

Table 7.4 Comparison-of-means test

Index	Tranquil period		Financial crisis and Arab Spring period		Test for equality of variances		T-test for equality of means	Evidence of impact of contagion
	Mean	Std. dev.	Mean	Std. dev.	*F*	Sig		
South Africa market	0.752449	0.17073	0.79469	0.16304	0.257	0.612	2.521	NO
Emerging African market	0.70811	0.15203	0.84456	0.23587	36.016	0.000	6.270***	YES
Emerging African market excluding South Africa	0.55912	0.16617	0.61021	0.21079	10.081	0.002	2.905**	YES
Frontier African market	0.20406	0.23643	0.31025	0.14327	34.440	0.000	4.897***	YES

Statistical significance at the 5% level indicates contagion for the Levine test of equality of variance, where the null hypothesis is equality of means. The reported t-test is appropriate for the variance identified. *, ** and *** are for 10%, 5% and 1% significance levels, respectively.

The comparison-of-means test shows identical findings to those from the dummy variable test and hence provides robustness for its findings. In terms of the level of significance, the two tests show exactly the same level of significance and hence this test verifies the findings in the dummy variable test.

7.6 Summary of findings

The objective of this chapter was to test for the stability of beta in the African markets. From the result within this section, I find that contagion has had a time-varying effect on beta within the South African market, the emerging African market and the emerging African market excluding South Africa. The result for the frontier African market is mixed. The instability in beta seen here is also reflected in Saleem and Viahenkoski (2010) and Tsai et al. (2014), who identify that the constant OLS beta does not capture the dynamics of beta. Others have highlighted that time-varying beta outperform the unconditional beta. I do, however, find that the outperformance of beta depends on the surveyed market. The dummy test and comparison-of-means test indicate that beta in the crisis period is significantly higher than those in the tranquil period within the emerging African market, the emerging African market excluding South Africa and the frontier African markets, but not in the South African market. This indicates the impact of contagion on these markets (except South Africa). The charts within the South African market show a couple more spikes beyond the period defined as the contagions period and this is the potential explanation for the insignificant result. In observing the conditional variable charts, it is clear that the conditional variables fluctuate over time, with clear spikes around the financial crisis and/or the Arab Spring. In their analysis of some developed and emerging market countries, Long et al. (2014) found some contagion effects similar to the findings within this study.

7.7 Chapter conclusion

The main purpose of this chapter was to check the stability of beta in the emerging and frontier African markets, along with the South African market and the emerging African market excluding South Africa. The more robust GARCH-type models are used to control for heteroscedasticity and to model conditional beta in the markets sampled. The results show that beta is not stable in the frontier market index, but the high parameter values in the South African market, the emerging African market and the emerging African market excluding South Africa did not show any significance.

However, the instability in beta across the indices seemed obvious with a visual observation of the conditional beta charts. These are also found from observing the conditional correlation, conditional covariance and conditional variances. It is generally expected that during crisis periods, variance, covariance, correlation and, to a lesser extent, beta of financial returns increase dramatically; hence I observe spikes around the financial crisis period and also around the Arab Spring for most markets. Although there were also other mostly smaller spikes within each index, the spikes are, however, not consistent across the indices surveyed.

The graphical results also show a reverse behaviour of beta, as the mean conditional beta in the frontier African market (0.23) was far lower than beta in the emerging African market (0.74). This was also observed in the unconditional beta discussed in Chapter 6. This is attributed to a reverse integration effect where indices in the African continent show characteristics that are not in line with those in the Western markets until after some degree of integration is achieved.

In testing for contagion, this study employs the dummy variable test and for robustness, the comparison-of-means test. The results for both tests are identical and show evidence of contagion in the emerging African market, the emerging African market excluding South Africa and the frontier African market. However, no evidence of contagion was found in the South African market due to the interdependence of the South African market and the Western markets.

7.8 Chapter appendices

Appendix 1: Proof of correct identification of time-varying beta

Original model

Model 1: OLS
Dependent variable: PORT

	Coefficient	*Std error*	*t-ratio*	*p-value*	
const	28470.4	1911.48	14.8944	<0.00001	***
MARKET	0.055904	0.00569477	9.8167	<0.00001	***
SIZE	-170.509	66.1109	-2.5791	0.01379	**
MOM	***-55.1351***	24.5861	-2.2425	0.03068	**

Replicate MOM beta - First mean equation

Model 2: OLS
Dependent variable: PORT

	Coefficient	*Std error*	*t-ratio*	*p-value*	
const	32025.1	1120.75	28.5747	<0.00001	***
MARKET	0.0434583	0.00133937	32.4469	<0.00001	***
SIZE	-217.77	65.7419	-3.3125	0.00197	***

Second mean equation

Model 3: OLS, using observations 1969-2011 (T = 43)
Dependent variable: MOM

	Coefficient	*Std error*	*t-ratio*	*p-value*	
const	-64.4725	6.86991	-9.3848	<0.00001	***
MARKET	0.000225731	8.20997e-06	27.4948	<0.00001	***
SIZE	0.857185	0.402981	2.1271	0.03963	**

Residuals from two mean equations

Model 4: OLS, using observations 1969-2011 (T = 43)
Dependent variable: uhat2

	Coefficient	*Std error*	*t-ratio*	*p-value*	
uhat3	***-55.1351***	23.6917	-2.3272	0.02485	**

The coefficient -55.1351 in the regression above (Model 4) is calculated as Cov(x,y)/Var(x). If the Cov(x,y) and Var(x) are time-varying, then we can possibly get a time-varying coefficient.

Table A 7.1 Mean equations with robust standard errors

	South Africa		Emerging Africa		Emerging Africa ex. SA		Frontier Africa	
Variable	r_{it}	r_{ij}	r_{it}	r_{ij}	r_{it}	r_{ij}	r_{it}	r_{ij}
$\boldsymbol{\alpha}$	−0.140414	−0.138663 *	−0.379823***	−0.185208***	−0.659568***	−0.434355**	0.246544*	0.328681**
$\boldsymbol{\mu_{is}}$	−0.531814 ***	−0.152598***	0.0717933	−0.0325135	−0.260251***	−0.100150*	0.0330483	−0.0410139***
$\boldsymbol{\mu_{ih}}$	−0.000672588	−0.0241135	-0.0835153	−0.00275418	0.106120*	0.0673308	0.0580786**	0.0230112
$\boldsymbol{\mu_{im}}$	0.0683822	0.0340642	0.0617514	0.0421787	0.387257***	0.334895***	0.0447139**	0.00995168
$\boldsymbol{\mu_{ip}}$	−0.408432 ***	−0.115049*	-0.154121***	−0.146608***	0.0289312	−0.0722888	−0.0316438	0.0316064*
$\boldsymbol{\mu_{isk}}$	−0.000979672	−0.00114582	-0.000163795	0.000259961	−0.00165167	−0.00395748	0.00164275	−0.00218731**
$\boldsymbol{\mu_{ik}}$	0.144201	0.144529*	0.384491***	0.190154***	0.662448 ***	0.439998**	−0.246129*	−0.323979**

*, ** and *** indicates statistical significance of the coefficient at the 10%, 5% and 1% levels.

Table A 7.2 DCC equations for South Africa, Emerging Africa, Emerging Africa ex SA and Frontier Africa

South Africa - GJR (1,1)	Parameter	T-value	T-probability	Log likelihood
Rho	0.509405	12.58	0.0000	
Alpha	0.023376	1.095	0.2738	
Beta	0.906806	7.883	0.0000	2798.603
Emerging Africa - GJR (1,1)	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.551048	13.63	0.0000	
Alpha	0.029311	1.553	0.1211	
Beta	0.909351	13.10	0.0000	3067.472
Emerging Africa ex SA - GARCH (1,1)	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.546280	13.28	0.0000	
Alpha	0.095264	1.330	0.1840	
Beta	0.718306	2.685	0.0075	3003.352
Frontier Africa – GARCH (2,1)	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.031194	0.5490	0.5832	
Alpha	0.014504	2.685	0.0075	
Beta	0.985486	146.2	0.0000	3260.201

Rho is the correlation targeting parameter.

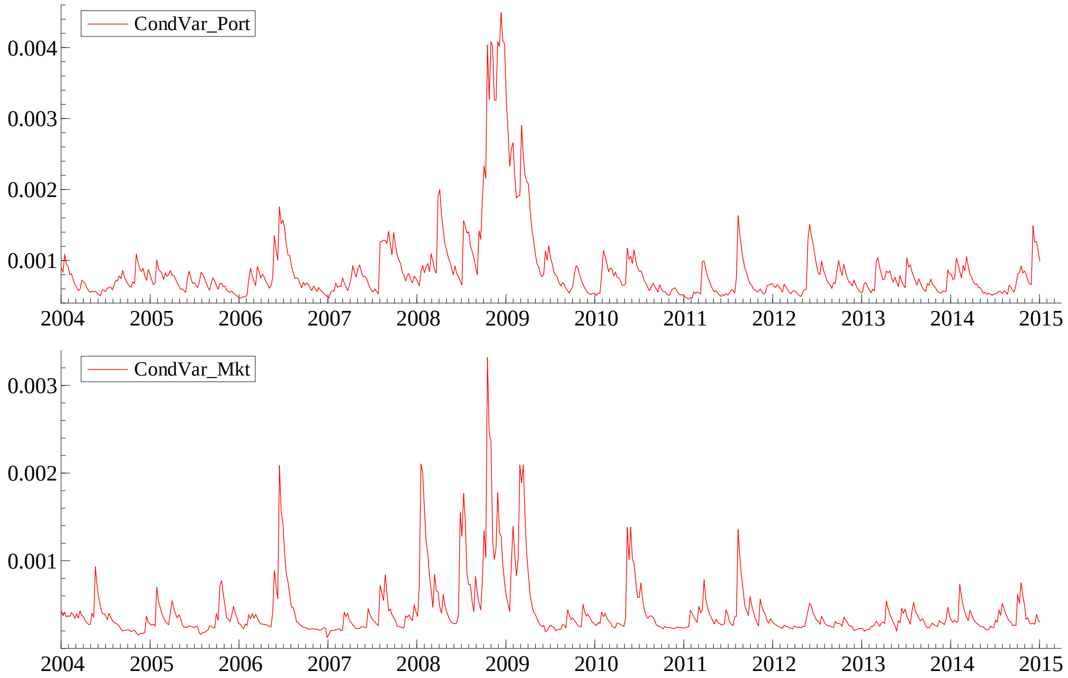
Table A 7.3 Autocorrelation tests for mean equations. Q-statistics on standardised residuals of South Africa, Emerging Africa, Emerging Africa ex SA and frontier Africa

South African market - asset portfolio	South African market - mkt portfolio
Q(5) = 5.90232 [0.3158402]	Q(5) = 5.96691 [0.3094522]
Q(10) = 14.9605 [0.1335089]	Q(10) = 13.9421 [0.1756496]
Q(20) = 23.5250 [0.2637576]	Q(20) = 21.8302 [0.3497960]
Q(50) = 51.7500 [0.4053443]	Q(50) = 63.5350 [0.0945950]
Emerging African market - asset portfolio	**Emerging African market -mkt portfolio**
Q(5) = 8.66259 [0.1233029]	Q(5) = 3.57667 [0.6118188]
Q(10) = 9.21580 [0.5117530]	Q(10) = 11.1591 [0.3452580]
Q(20) = 24.8956 [0.2054549]	Q(20) = 16.9523 [0.6560678]
Q(50) = 62.9696 [0.1030022]	Q(50) = 65.7448 [0.0668940]
Emerging African market ex. South Africa - asset portfolio	**Emerging African market ex. South Africa - mkt portfolio**
Q(5) = 3.13922 [0.6785319]	Q(5) = 4.80168 [0.4405605]
Q(10) = 5.27163 [0.8723103]	Q(10) = 10.8675 [0.3679366]
Q(20) = 10.7992 [0.9512644]	Q(20) = 19.3447 [0.4995293]
Q(50) = 33.8098 [0.9614656]	Q(50) = 55.5274 [0.2743414]
Frontier African market - asset portfolio	**Frontier African market - mkt portfolio**
Q(5) = 5.81901 [0.3242302]	Q(5) = 61.1376 [0.0000000]
Q(10) = 10.3948 [0.4065629]	Q(10) = 91.5194 [0.0000000]
Q(20) = 24.5324 [0.2199084]	Q(20) = 120.064 [0.0000000]
Q(50) = 65.7627 [0.0667002]	Q(50) = 157.618 [0.0000000]

Table A 7.4 Autocorrelation tests for means equations. Q-statistics on squared standardised residuals of South Africa, Emerging Africa, Emerging Africa ex SA and frontier Africa

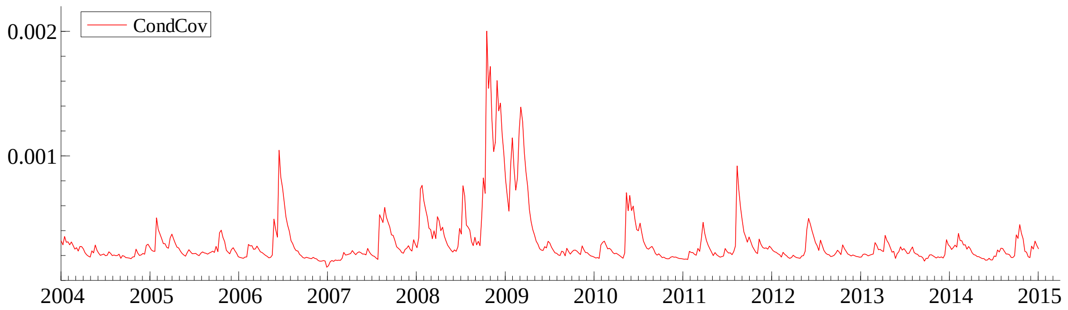
South African market - asset portfolio	**South African market - mkt portfolio**
Q(5) = 1.25559 [0.9394341]	Q(5) = 1.86412 [0.8676086]
Q(10) = 3.34404 [0.9721304]	Q(10) = 7.70491 [0.6576360]
Q(20) = 14.9616 [0.7785979]	Q(20) = 14.8309 [0.7860004]
Q(50) = 47.3396 [0.5807779]	Q(50) = 65.3152 [0.0716754]
Emerging African market - asset portfolio	**Emerging African market - mkt portfolio**
Q(5) = 1.77502 [0.8793167]	Q(5) = 4.56893 [0.4707142]
Q(10) = 8.66997 [0.5636845]	Q(10) = 9.76135 [0.4616748]
Q(20) = 24.7974 [0.2092940]	Q(20) = 24.6055 [0.2169430]
Q(50) = 56.3165 [0.2505030]	Q(50) = 72.4254 [0.0207225]
Emerging African market ex. South Africa - asset portfolio	**Emerging African market ex. South Africa - mkt portfolio**
Q(5) = 1.68383 [0.8909302]	Q(5) = 1.84968 [0.8695290]
Q(10) = 3.14094 [0.9779099]	Q(10) = 3.53786 [0.9657971]
Q(20) = 24.9801 [0.2021953]	Q(20) = 6.73677 [0.9974633]
Q(50) = 58.9954 [0.1797231]	Q(50) = 26.0817 [0.9979235]
Frontier African market - asset portfolio	**Frontier African market - mkt portfolio**
Q(5) = 7.33076 [0.1971804]	Q(5) = 3.73281 [0.5884890]
Q(10) = 10.3222 [0.4126928]	Q(10) = 9.96903 [0.4432148]
Q(20) = 21.1315 [0.3894305]	Q(20) = 14.8388 [0.7855563]
Q(50) = 70.1393 [0.0315747]	Q(50) = 46.8959 [0.5987066]

Figure A 7.1 Conditional variance for the South African market asset and market portfolios



Mean conditional variance for the asset and market portfolios are 0.00087039 and 0.000428971, respectively.

Figure A 7.2 Conditional covariance for the South African market

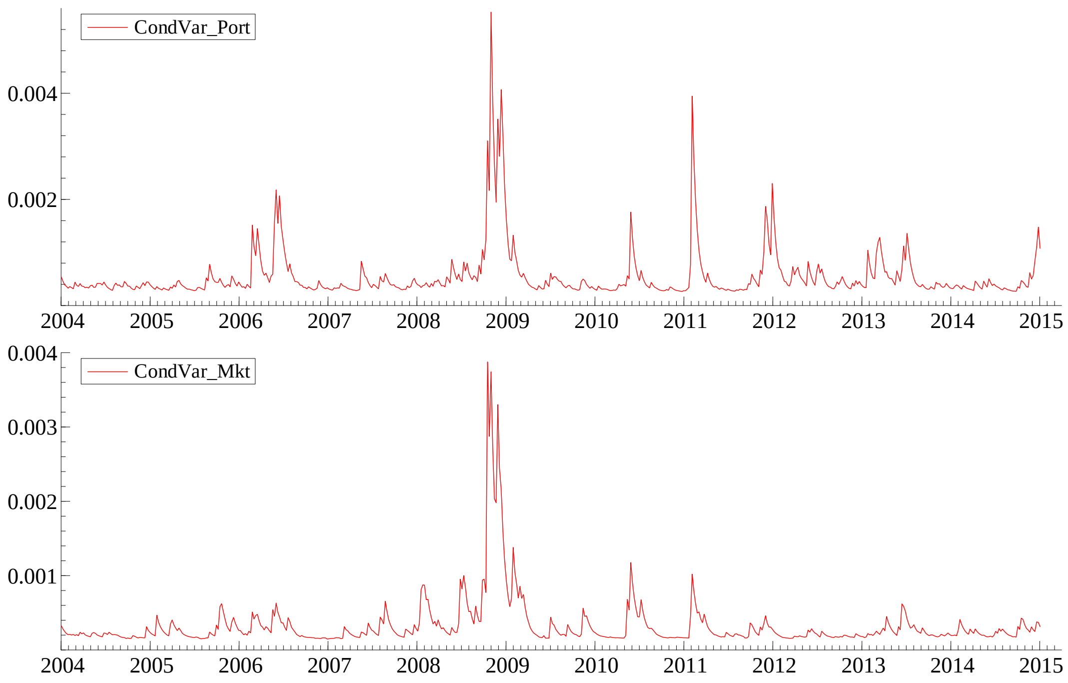


Mean conditional covariance is 0.000306807

Figure A 7.3 Conditional correlation and conditional beta for the South African market

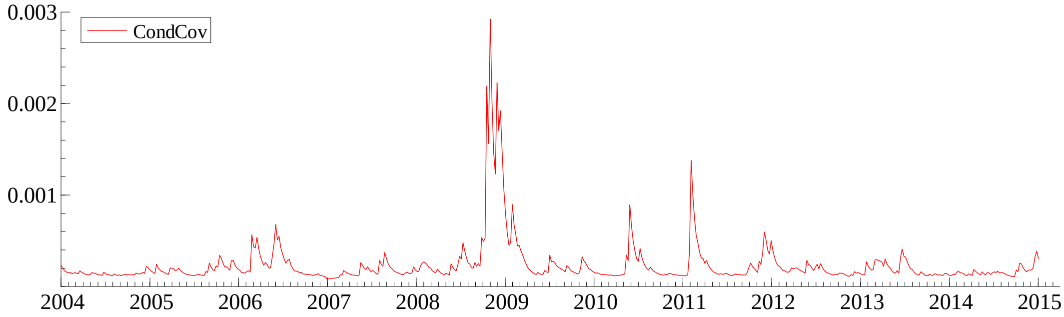
Mean conditional correlation and conditional beta are 0.50730371 and 0.762146409, respectively.

Figure A 7.4 Conditional variance for the emerging African market asset and market portfolios.



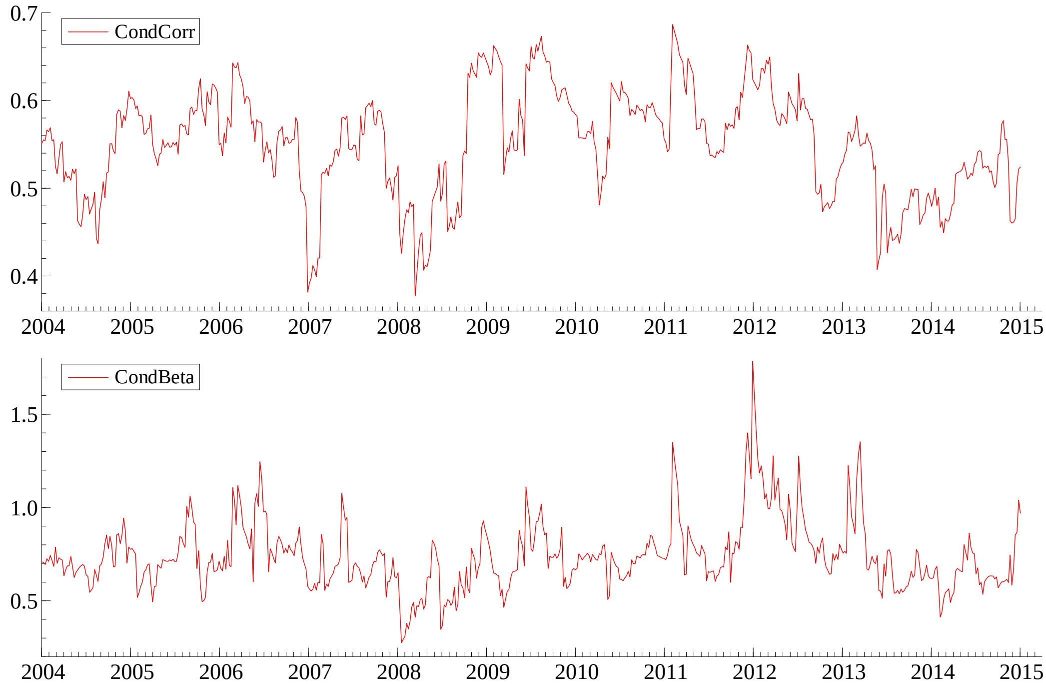
Mean conditional variance for the asset and market portfolios are 0.000551695 and 0.000329728, respectively.

Figure A 7.5 Conditional covariance for the emerging African market



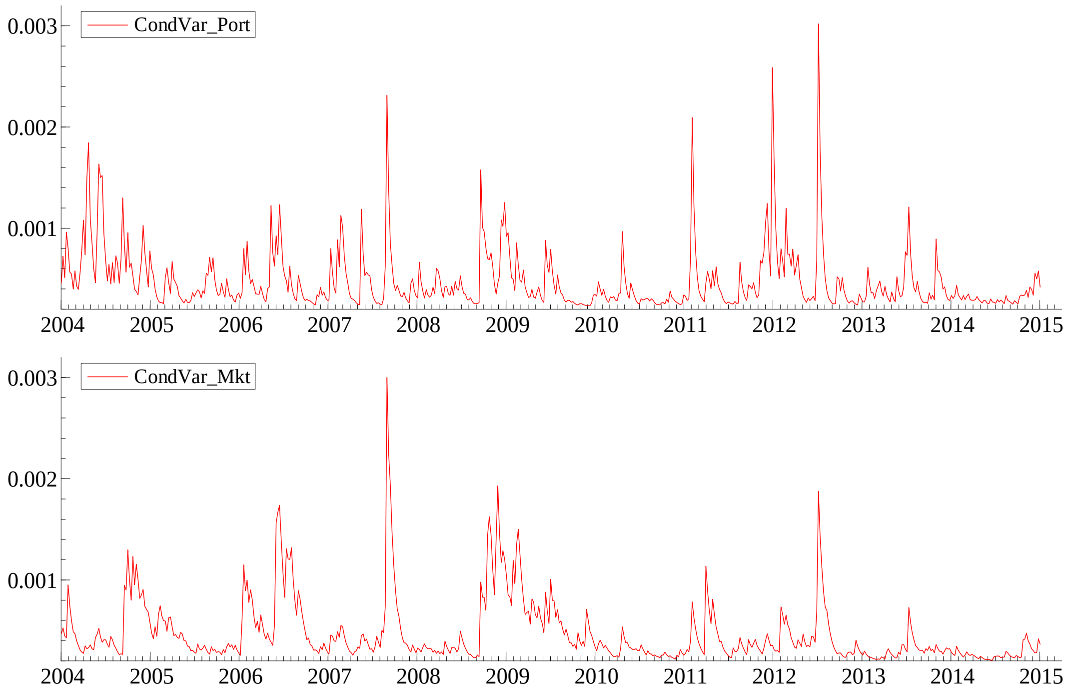
Mean conditional covariance is 0.000235691

Figure A 7.6 Conditional correlation and conditional beta for the emerging African market



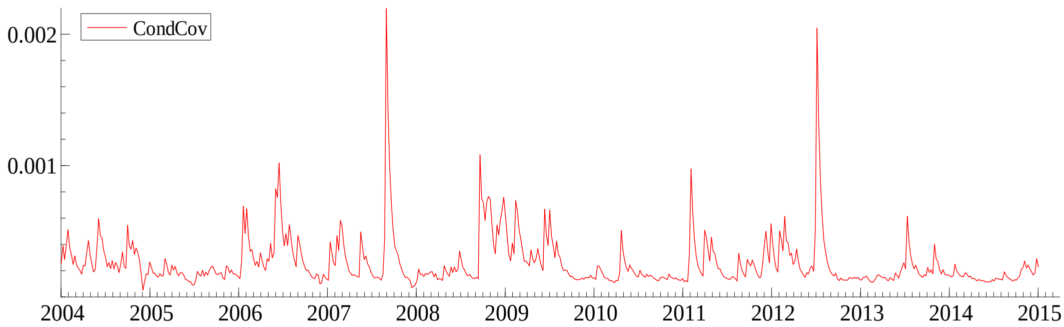
Mean conditional correlation and conditional beta are 0.550318985 and 0.739438166 respectively.

Figure A 7.7 Conditional variance for the emerging African market excluding South Africa asset and market portfolios



Mean conditional variance for the asset and market portfolios are 0.000477373 and 0.000474072, respectively.

Figure A 7.8 Conditional covariance for the emerging African market excluding South Africa

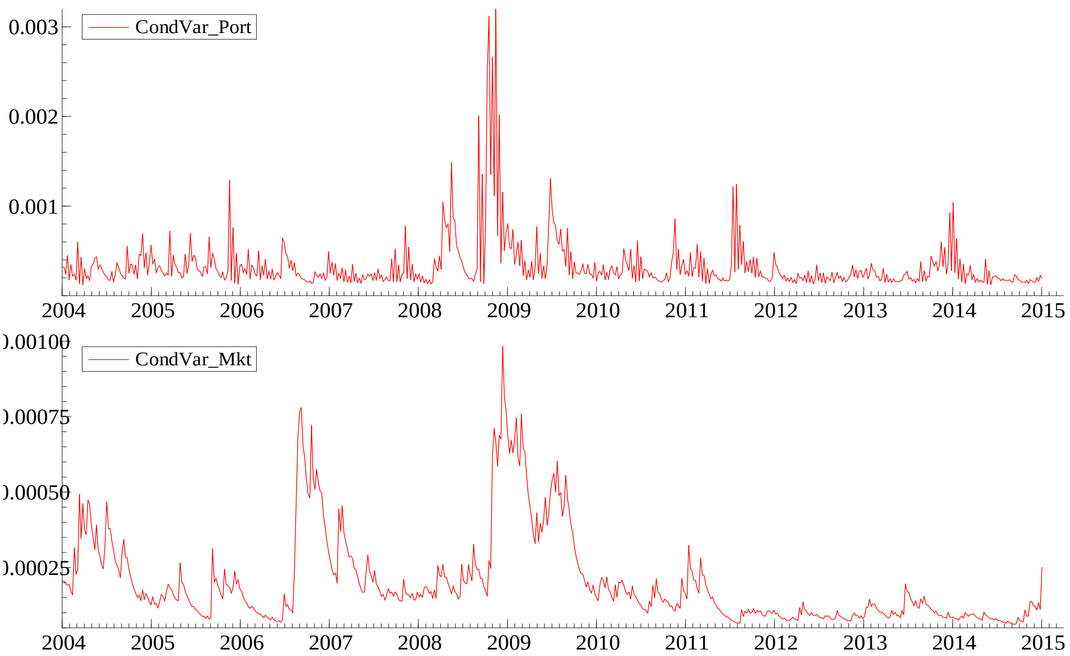


Mean conditional covariance is 0.000262483

Figure A 7.9 Conditional correlation and conditional beta for the emerging African market excluding South Africa

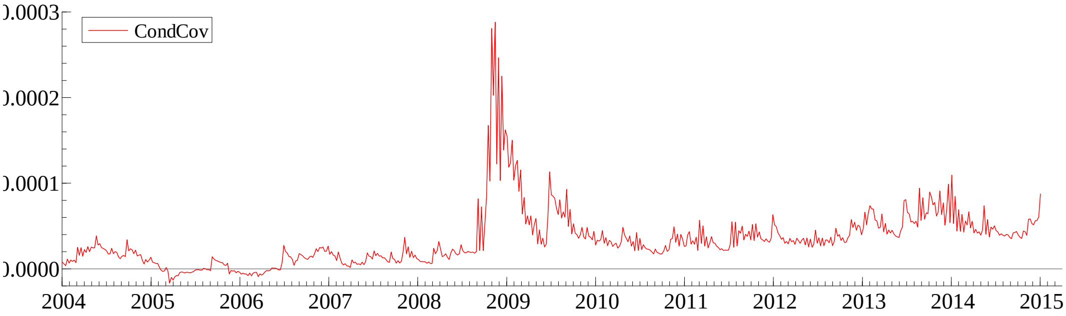
Mean conditional correlation and conditional beta are 0.548502369 and 0.570847856, respectively.

Figure A 7.10 Conditional variance for the frontier African market asset and market portfolios



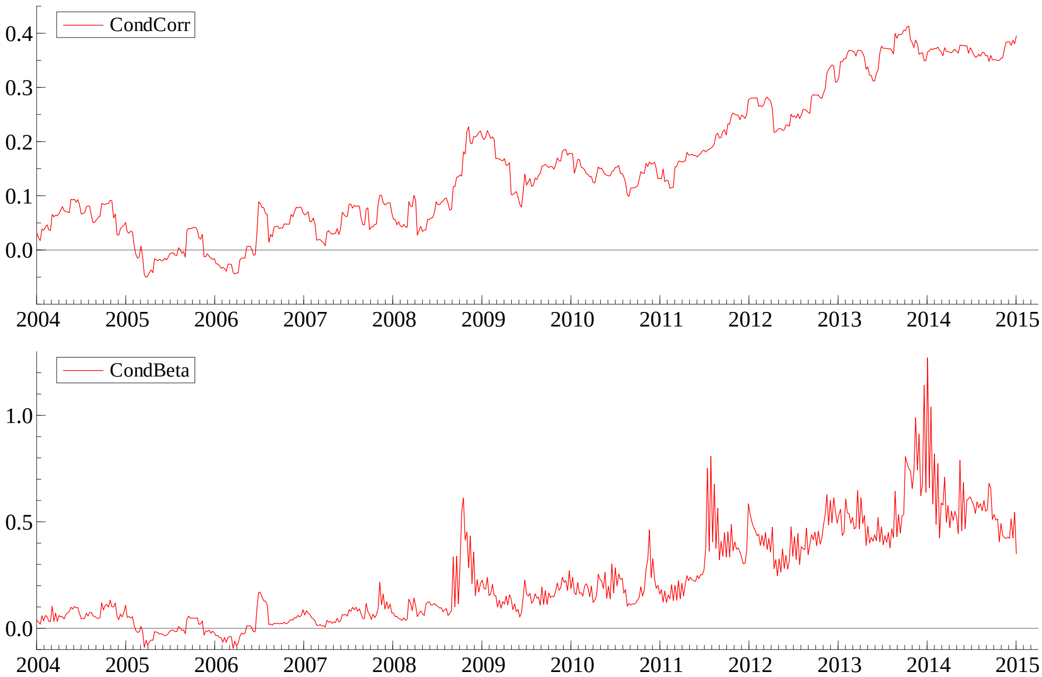
Mean conditional variance for the asset and market portfolios are 0.000331507 and 0.000202341, respectively.

Figure A 7.11 Conditional covariance for the frontier African market



Mean conditional covariance is 0.00003377

Figure A 7.12 Conditional correlation and conditional beta for the frontier African market



Mean conditional correlation and conditional beta are 0.157209141 and 0.228433412, respectively.

8 CONCLUSION, THESIS CONTRIBUTION, LIMITATION OF THE RESEARCH AND AREAS OF FURTHER RESEARCH

8.1 Introduction

The deregulation of markets and relaxation of capital controls within the African continent are fuelling the growth in international investment among private and institutional investors. With this growing importance of the African equity market, the need for a comprehensive asset-pricing study became paramount. The overriding aim of this research was to achieve just that, a comprehensive asset-pricing study within the African continent.

To capture the characteristics of the African market, I employ data from the resource sector within the surveyed markets. This is done because African markets are mainly resource-driven, with activities within this sector driving most other sectors and hence the economy.

To achieve a robust analysis, data problems in the African market had to be addressed. To do this, the data was expunged of survivorship bias using the CRSP methodology and subsequently indices were formed based on the FTSE quality of market criteria (AFRICA) of March 2014. These indices allowed for the problem of infrequent daily data to be overcome and had the added benefit of providing a diversification advantage.

The indices are the emerging African market index and the frontier market index. I formed a further two indices – the South African market and the emerging African market index excluding South Africa, to isolate the possible blurring impact of the largest African market – South Africa. I employed this classification because I expected differences in the results within these markets.

My thesis analyses deeply the factor that explains realised returns using the Sharpe-Lintner CAPM, the Fama-French three-factor model, the Carhart four-factor model and the liquidity- and higher-moments augmented models, providing a unique perspective within the indices created.

The 2008 financial crisis and the Arab Spring provided the opportunity to test for the impact of contagion on asset-pricing estimates, in the African market. This has not been done comprehensively in the African market in the past. This also gives researchers the opportunity to explore in more detail the importance of accounting for exogenous factors in asset-pricing models.

8.2 Summary of the main findings of the thesis

In identifying potential factors that are important in African CAPM-type models, I evaluated the key literature within the asset pricing and the African market (Chapter 2). As part of this process of identifying gaps in the literature, I identified the following potential novel contribution as: *1) evaluating the magnitude and potential impact of survivorship bias of estimates of the asset-pricing models; 2) examining which of the alternative factor models is best suited for the South African market, the emerging African market, the emerging African market excluding South Africa and the frontier African market; 3) analysing the importance of beta, size, book-to-market value, momentum, liquidity and higher-order moments (coskewness and cokurtosis), in explaining realised returns; 4) examining the impacts of contagion on estimates of the unconditional and conditional asset-pricing models*.

Chapter 3 discussed the data problems and sample selection. The dataset consisted of four indices: the South African market index, the emerging African market index, the emerging African market index excluding South Africa and the frontier African market index. The emerging African market index consists of South Africa, Egypt and Morocco, while the frontier African market consists of Botswana, Cote d'Ivoire, Kenya, Nigeria and Tunisia.

In analysing the impact of contagion, I identified two shocks –the 2008 financial crisis and the Arab Spring. This was done using the timeline of events and the CBOE market volatility index (VIX). I applied the DCC GARCH approach with the objective of identifying whether the contagion factors had a time-varying effect on the estimates of beta with the sampled indices. Other potential alternative methodologies are also assessed in Chapter 3, Section 3.8.6, with the DCC GARCH being the preferred method. The expectation was that contagion will affect beta across all the indices formed, although the effect may vary across these indices.

The impact of survivorship bias was expected to be higher within the African market when compared with findings in developed markets. Hence I identified in Chapter 3, Section 3.4, the methods through which the survivorship bias will be eliminated from the data. The CRSP methodology was preferred over Heckman's two-equation method, due to the limitations of Heckman's two-equation method as highlighted in Chapter 3, Section 3.4.1.

Chapter 4 evaluates the magnitude and potential impact of survivorship bias on estimates of asset-pricing models, using the Jensen alpha approach identified in Rohleder, Scholz and Wilkens (2011) and the mean difference approach of Eling (2008). This chapter also goes on to estimate the attrition rate of stock within the index and establish a link between the attrition rate and survivorship bias. This was based on the emerging African market index and, for robustness, the South African market index, as this chapter was for demonstration of the impact of survivorship bias. Survivorship bias was, however, corrected for in all the indices used.

8.2.1 Key findings

The thesis finds average survivorship bias of 297.47 basis points per year for the basic materials emerging African index stocks (January 2005 to December 2014), and 731.05 basis points per year for the basic materials South African index stocks, over the same period, using the Jensen alpha methodology highlighted in Rohleder, Scholz and Wilkens (2011). This can be compared with the 157 basis points per year reported in Rohleder, Scholz and Wilkens (2011), using data from the US domestic equity mutual fund market (1993 to 2006), with lower values reported in other developed markets (Deaves, 2004).

Using the mean difference methodology, as identified in Eling (2008), I find survivorship bias of 359 basis points per year for the basic materials emerging African index stocks (January 2005 to December 2014). For the basic materials South African index the corresponding survivorship bias was 544 basis points per year, during the same time period. These values are also high when compared to previous studies that applied the same methodology, as seen in Brown, Goetzman and Park (2001) and Amin and Kat (2003), who find survivorship bias between 60 and 360 basis points per year and 200 basis points per year, respectively, both in the US market.

Attrition rates are directly related to survivorship bias; a low attrition rate will lead to low survivorship bias, as identified in Liang (2000). This study finds the average attrition rate in the emerging African market to be much higher (12%) than those found in US studies (for example, Carpenter and Lynch, 1999, found an attrition rate of 3.6%). My research therefore calls into question previous studies on asset pricing in African markets that do not adjust for survivorship bias.

Within the South African market, beta was found to be positive and statistically significant for the standard, the three-factor and four-factor CAPMs. But unlike most studies that identify a size premium, I found size to be negative and statistically significant, indicating that large firms outperform small firms. The book-to-market value and momentum factors were insignificant, while the liquidity factor was significant but had a negative relationship with returns. The higher moments of returns distribution are not priced in the South African basic materials index; however, I found that the contagion dummy was negative and significant, indicating that extreme shocks have a negative relationship with returns. The results do indicate that the liquidity-augmented four-factor model that controls for contagion performs better within the South African market.

Within the emerging African market, I found beta, size and cokurtosis to be positive and significant while book-to-market value, momentum, liquidity and coskewness were insignificant. The dummy variable for contagion was found to be significant within the liquidity-augmented four-factor model that controls for contagion, but insignificant when higher moments are included. The findings also indicate that the liquidity-augmented four-factor model that controls for contagion performs better within the emerging African market.

I also examined the performance of the emerging African market when the South African market is excluded and found that beta (positive), size (negative), book-to-market value (positive), momentum (positive), liquidity (positive) and cokurtosis (positive) were all significant, while coskewness was insignificant. The liquidity-augmented four-factor model also performs best within the emerging African market less South Africa.

I also found that the models perform better in the emerging African market excluding South Africa, than when South Africa is included, and this is due to the significant difference in the level of integration of the South African market, compared with the Egyptian and the Moroccan markets.

Within the frontier African market, beta was significant across all models while size (positive) and value (positive) were insignificant within the three-factor model, but were significant when the momentum factor was introduced, with the momentum (positive) factor also significant. I found liquidity to be unimportant within the frontier African market, with the contagion-effect variable being negative and significant, demonstrating the impact of the financial crisis and the Arab Spring on the frontier African market's index performance. However, unlike the findings above, the higher-moment augmented model performs better within the frontier African market, with the coskewness measure being significant but the cokurtosis measure being insignificant.

In comparing performance of the models across all the four indices, I found significant differences across all four market indices as expected, due to the varying levels of integration with world markets. I found that beta is consistently positive and significant, indicating that beta is alive and well in the African market. I found that size and liquidity are significant, but their direction depends on the characteristics of the surveyed market. However, I found that value and momentum factors have a positive relationship with returns, but their importance depends on the level of integration with world markets.

For higher moments, I found that the coskewness measure is only important in the frontier African market, while the cokurtosis measure is important in an emerging African market context (including when South Africa is excluded). For the contagion dummy, there seems to be an offsetting effect between the dummy and higher-order moments in emerging African markets; otherwise contagion is negative and significant.

Time-varying beta: in comparing the results across the GARCH-type models, I found beta in the frontier African market to be unstable, while the high parameter value in the South African market, the emerging African markets and the emerging African market excluding South Africa showed no significance. However, a visual representation of the conditional beta, conditional correlation, conditional covariance and conditional variances showed instability within the time period studied. The results also show marked differences between the emerging and frontier African markets, with the mean conditional beta being 0.23 in the frontier market, compared with 0.74 in the emerging African market. This is, however, consistent with the pattern observed within the unconditional beta estimates.

In testing the impact of contagion on the African indices, I employed a dummy variable test and, for robustness, a comparison-of-means test. The results show some evidence of contagion in the emerging African index, the emerging African index excluding South Africa and the frontier African market index. However, no evidence of contagion was found in the South African market due to its interdependence with Western markets.

8.3 Novel contributions

The novel contributions of my research to asset pricing in the Africa market include the following.

The thesis has added to the body of knowledge in the African market through a detailed analysis of the magnitude of survivorship bias in the emerging African market. Survivorship bias was found to be much higher in the African market when compared to studies in developed markets. But, in line with other studies, attrition rate was found to be directly related to survivorship bias.

The thesis has also contributed to the literature through a comprehensive analysis of asset-pricing models using indices formed on African stocks. I find that the liquidity-augmented four-factor model, which accounts for the contagion effect, performs best in the South African market, the emerging African market and the emerging African market excluding South Africa, while the higher-moment and liquidity-augmented four-factor model, which accounts for the contagion effect, performs best in the frontier African market. The thesis finds significant differences in the factors that determine returns across the South African, emerging and frontier African markets, which highlights the tendency for the determinants to change with the degree of integration with Western markets, although with significant peculiarities on the direction of some of the variables within the African market.

The thesis has demonstrated the time-varying nature of beta in the markets studied. It has also shown the impact of contagion on conditional beta within the African market indices. The results show that beta is not stable in the frontier market index, but the high parameter values in the South African market, the emerging African market and the emerging African market excluding South Africa did not show any significance. However, the instability in beta across the indices seemed obvious with a visual observation of the conditional beta charts. These are also found from observing the conditional correlation, conditional covariance and conditional variances.

8.4 Recommendations for stakeholders

Professional fund managers: As demonstrated in Chapter 1, the growth in the African stock market is mostly greater than in the developed markets and hence provides a good source of capital gains. As seen in Chapter 6, asset-pricing determinants vary across the continents and do depend on the level of integration with world markets. Also, I identified variations in conditional correlation and conditional beta within the African markets, as seen in Chapter 7. This shows, for example, a very low mean conditional beta of *0.23* in the frontier African market, hence providing diversification advantages.

Academic researchers: This thesis provides a more comprehensive asset-pricing study within the African market, but also identifies potential areas of future research, which are highlighted below.

Regulators/policy-makers: This thesis identifies some liquidity effects that may also be a source of contagion as relatively small and illiquid markets may reflect the fact that markets contain a relatively small number of active traders. Hence more liquidity could minimise any adverse impacts of contagion. The continued opening of markets to foreign investors will be a good way to ensure increased liquidity. Also, liquidity can be improved by integrating the operations of African stock markets. This will also enhance operational effectiveness and more efficient allocation of capital and, consequently, a positive impact on economic growth.

In regulating activities within various sectors, it will be beneficial to measure time-varying beta in comparison to static beta as this study shows that beta may not be static, especially in the frontier African market.

8.5 Limitations of the research

Even with this study being performed on a large number of African markets (South Africa, Egypt, Morocco, Botswana, Kenya, Nigeria, Tunisia and a regional market – BRVM in Cote d'Ivoire, which covers the markets in Benin, Burkina Faso, Guinea Bissau, Mali, Niger, Senegal and Togo), there are still other markets that were not covered. This was mainly due to lack of data, as seen in Ghana and Mauritius, for example. Secondly, given that comparable risk-free rates in the African markets are often not risk-free and sometimes far higher than returns on equity, I have not used them in my asset-pricing estimates. I have however used the US 3-month Treasury bill (US3MT=RR), adjusted to obtain weekly short-term rates. This is suitable for the purpose of this analysis as it has been applied in other studies on the African market, as seen in Omran (2007).

8.6 Potential future research areas

Following the findings within this thesis, potential future research areas can include the following.

8.6.1 Other sectors in the African market

I identify that the natural resources sector in the African continent is the major sector as activities within this sector drive most other sectors and hence the economy. However, given the mix of sectors within the African market, a natural extension will be to investigate other sectors such as consumer goods, consumer services, financials, healthcare and technology. This may reveal different dynamics in play as, for example, I expect volatility to be higher within these sectors when compared to the resources sector, as these sectors have firms with traditionally lower market capitalisation than the natural resources firms. However, there may be some serious data availability problems in doing this, as many of these sectors have very young companies.

8.6.2 Liquidity measure

Chapter 2, Section 2.4 evaluates the liquidity measures that can be potentially applied in the African market and Chapter 3, Section 3.8.2 justifies the use of the bid/ask measure of liquidity. This follows Lesmond (2005), who indicates that the most demonstrable indicator of overall liquidity still remains the bid-ask quote. Also, given data scarcity in the African market, I naturally used the bid-ask quotes as the values required were available. Other measures of liquidity can also be applied to account for other dimensions of liquidity; these include the standardised turnover-adjusted number of zero trading days in Liu (2006), the daily ratio of absolute stock returns to dollar volume measure in Amihud (2002) and the liquidity measure following Pástor and Stambaugh (2003). Other liquidity measures are highlighted in Lam and Kim (2011) and these include simple turnover ratio, simple trading volume, standard deviation of turnover ratio, standard deviation of trading volume, the coefficient of variation of turnover and the coefficient of variation of trading volume. Data on turnover and trading volume data are, however, inconsistent across African markets.

8.6.3 Bull and bear CAPM

Another direction in examining asset pricing in the African market is through the use of asymmetric betas, i.e., estimating beta for the bull and bear market phases respectively as seen in Chong, Pfeiffer and Phillips (2011). This may be useful in the African market as there may be some distortionary effect in single unconditional betas arising from up- and downturns in the market. This is because, the prevalent use of one estimate of beta for both up- and downturns in the market can lead investors to oversimplify the risk characteristics of the investment in the African market. Some previous research, like those of Chong, Pfeiffer and Phillips (2011) have explored the dual-beta model’s efficacy in containing risk during stock market downturns and found it superior to the standard CAPM beta.

8.6.4 Potential alternative methods for modelling time variation

As identified in Chapter 3, Section 3.8.6, there are a wide range of alternatives in modelling time variation in beta that can be applied depending on market characteristics assumptions. These alternatives include the threshold CAPM where asset betas change with respect to investors' assessment of aggregate risk conditions, hence a slower variation in beta than the conditional CAPM suggests. Another alternative is the Kalman filter-based approach where the time-varying structure of the beta can be modelled directly through a state space approach. Another alternative is the stochastic volatility approach, which adds contemporaneous shock to the return variance. Another potential alternative is the Markov switching approach, which is also known as the regime-switching model within a broader class of state space models. It normally involves the characterisation of the time-series behaviours of different regimes using multiple structures (equations). By allowing the switching between these structures, the model is able to capture more complex dynamic patterns.

8.6.5 Behavioural finance in the African market

As identified in Section 2.2.7, there seems to be a paradigm shift occurring in recent years in the study of stock market behaviour and this shift is changing the direction of research from the study of the financial environment to the agents of this environment. This has become apparent due, in part, to the poor performance of the weak-form efficient market hypothesis, especially in the African market as reported in Ntim, Opong and Danbolt (2007). This questions the central tenet of the modern financial paradigm which assume that security prices adjust rapidly to the arrival of new information, hence current prices of securities reflect all information about the security. This follows that investors act rationally and expectedly consider all available information in portfolio investment decision process. Recent evidence, however, suggests that this is not always the case hence; the efficiency of markets has become one of the most controversial arguments in finance literature, along with the behaviour of agents.

As also highlighted in Section 2.2.7, other variants of the CAPM include those from the standpoint of behavioural finance and psychology, where proponents argue that the psychology of the investors affects their perception of risk specifically, but also investment behaviour in general, hence affecting expected returns. Andrikopoulos (2007), for example, investigated the overreaction and underreaction hypothesis and conclude that they are the two most important hypotheses that can partially explain the price equilibrium anomalies. Specifically, Bernard (1992) highlight that stock prices underreact to earnings announcement with a “post-earnings announcement drift” resulting from a subsequent completion of the reaction in stock prices.

The tendency to overreact and deviate from Bayesian, optimum, rational decision-making arises from psychological biases such as representativeness, anchoring and adjustment, leniency and conservatism heuristics, as seen in Kahneman and Tversky (1973). The expectation is that relative underreaction/overreaction will be more in the African market due to delay in information dissemination given unsophisticated information channels. This will result to holding period returns which arises because of a delayed overreaction to information that pushes prices of winners above their long-term values and losers below their long-term values as Daniel et al. (1998) and Hong and Stein (1998) point out. I also expect this to be compounded by the problems of liquidity and thin trading within the African market.

Given the peculiarity of the African market, I expect the following behavioural biases and heuristics to have some effect of asset pricing: ambiguity aversion, mood and feelings and self-deception which imply overconfidence. There are also increasing interest in the effect of noise traders as seen in Blume and Easley (1992); while others highlight the impact of heuristic simplification (Dehnad, 2011). For an overview of the many other biases which could potentially have an impact on asset pricing in the African market, see Redhead (2011). Although I expect behavioural finance research in the African market to yield interesting results, the paucity of data will mean that this may take a while.

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