THE EFFICIENCY OF AFRICAN STOCK MARKETS: A COMPARATIVE ANALYSIS

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DECLARATION

Hereby I, Chipo Mlambo, declare that the research reported in this dissertation is my own work and is original, except where duly acknowledged. This dissertation has not been submitted previously, either in entirety or substantially, for a higher degree or qualification at any other university or institute of higher learning.

Chipo Mlambo
30 October 2009

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ABSTRACT

This study investigates whether any exploitable patterns exist in a sample of ten African stock markets that could lead to abnormal gains. Southern Africa is represented by Botswana, Namibia, Mauritius and Zimbabwe, East Africa by Kenya, West Africa by Ghana and the BRVM, and North Africa by Egypt, Morocco and Tunisia. Such evidence, if it exists, provides ground for refutation of the weak form of the efficient market hypothesis (EMH) as defined by Fama (1965, 1970).

The thesis is predominantly empirical, but also provides an overview of African stock markets, the theoretical framework on which the study is based and the impact of the advancement in information technology on market efficiency. It investigates whether the distribution of stock returns conforms to that of normality. The results show that the distribution of stock returns on African stock markets is not normal, and that the deviation from normality is significantly pronounced with almost all the stocks rejecting normality using the Kolmogorov-Smirnov test at the 1% level of significance.

The stock price behaviour of the abovementioned stock markets is investigated by testing the random walk hypothesis using the simple serial correlation and runs tests. The investigation is done using returns calculated on a trade-to-trade basis and adjusted for interval variability by weighting each trade-to-trade return by the number of days between trades. While the first part of this analysis only includes the markets on which dividend information could be obtained, the second part includes all the ten markets with returns referring to capital gains. However, it is shown that dividend information does not have a serious impact on the results. While the majority of stocks, especially those for Mauritius and Ghana, reject the random walk hypothesis, only Namibia, Kenya and Zimbabwe, can be said to be weak form efficient.

While thin trading is known to cause econometric and statistical problems in empirical tests, thin trading has been taken as given in most studies. In this thesis, the seriousness of thin trading on African stock markets and its implications for efficiency testing is empirically investigated. A comparison of the random walk test results when

returns are calculated normally and when the trade-to-trade approach and its variant, the adjusted trade-to-trade approach, are used is carried out. It is found that thin trading is indeed a severe problem on African markets and that there are some differences in the random walk results due to the different methods used to calculate returns.

Investigating in-sample predictability using linear models appears to be the norm in most tests of the EMH. This thesis argues that the return-generating process may not be linear and if that is the case, the nonlinear models may outperform the linear models in out-of-sample forecasting. The random walk is considered a true description of stock price behaviour only if it is not outperformed by any of the alternative models in forecasting stock prices out-of-sample. This is empirically tested using the indices data of the African stock markets in the sample. It is found that alternative models, in most instances, outperform the random walk model in out-of-sample forecasting.

The random walk results are substantiated by the results on seasonal patterns and other anomalies to the efficient market hypothesis such as the firm size and price-earnings (P/E) effects. Size and P/E ratios have been identified as significant predictors of stock returns in other markets. In particular, it has been suggested that small-size firm portfolios outperform large-size firm portfolios and that low P/E firm portfolios outperform high P/E firm portfolios. The size and P/E effects found in this thesis are mostly exactly the opposite of those hypothesised in the literature.

The existence of seasonal patterns contradicts the statement that stock prices behave in a random manner. This phenomenon is investigated on African stock markets using indices returns. The study benchmarks the findings with those of South Africa's Johannesburg Stock Exchange (JSE) Securities Exchange; other emerging markets, namely Brazil, Malaysia, Poland, Slovenia and Finland; and developed markets, such as the United States of America (U.S.), Australia and New Zealand. Seasonal effects are observed on some, but not all African stock markets and in most cases the patterns observed are different from those observed on stock markets elsewhere.

OPSOMMING

Hierdie studie delf na of daar enige ontginbare patrone in 'n proefstuk van tien Afrika aandelemarkte bestaan, wat tot abnormale winste kan lei. Suider-Afrika word deur Botswana, Namibië, Mauritius en Zimbabwe verteenwoordig; Oos-Afrika deur Kenia, Wes-Afrika deur Ghana en die BRVM, en Noord-Afrika deur Egipte, Marokko en Tunisië. Indien sodanige bewyse bestaan, sou dit as grondslag dien vir weerlegging van die prestasie van die doeltreffende mark-hipotese (EMH) soos deur Fama (1965, 1970) gedefinieer.

Die tesis is oorwegend empiries, maar bied ook 'n oorsig oor Afrika-aandelemarkte, die teoretiese raamwerk waarop die studie gebaseer is en die impak van die vordering in inligtingstegnologie op markdoeltreffendheid. Dit probeer vasstel of die verspreiding van winste op aandele met dié van normaliteit konformeer. Die resultate toon dat die verspreiding van winste op aandele op aandelemarkte in Afrika nie normaal is nie en dat die afwyking van normaliteit aansienlik skerp is met byna al die aandelemarkte wat normaliteit verwerp wanneer die Kolmogorov-Smirnov-toets (teen die 1%-vlak van beduidendheid) toegepas word.

Die gedrag van aandelepryse van bovermelde aandelemarkte is ondersoek deur die ewekansige steekproef-hipotese te toets deur die eenvoudige reeks korrelasie en aanvraag-toetse toe te pas. Die ondersoek is gedoen deur opbrengste te gebruik wat op 'n handel-tot-handel-grondslag bereken is en vir interval wisseling aangepas is deur iedere handel-tot-handel-opbrengs teenoor die aantal dae tussen transaksies op te weeg. Terwyl die eerste deel van die ontleding net die markte insluit waarop inligting oor dividende verkry kon word, het die tweede deel al tien markte ingesluit met opbrengste wat na kapitale winste verwys. Daar word egter bewys dat inligting oor dividende nie 'n ernstige en waardige impak op die resultate het nie. Terwyl die meerderheid aandele, veral dié vir Mauritius en Ghana, die ewekansige steekproef-hipotese verwerp, kan daar aanvaar word dat net dié in Namibié, Kenia en Zimbabwe swak-prestasie doelmatig is.

Terwyl dit bekend is dat swak handel statistiese en ekonometriese probleme in empiriese toetse meebring, is swak handel as 'n gegewe in die meeste studies aangedui. In die tesis word die erns van swak handel op aandelemarkte in Afrika en die implikasies daarvan vir doeltreffende toetsing empiries ondersoek. 'n Vergelyking van die resultate vir (ewekansige steekproewe) word getref wanneer winste normaal bereken word en wanneer die handel-tot-handel-benadering en sy variant, die aangepaste handel-tot-handelsbenadering, toegepas word. Daar is bevind dat swak handel inderdaad 'n ernstige problem op Afrika-markte is en dat daar sommige verskille in die ewekansige steekproef-resultate is as gevolg van die verskillende metodes wat ingespan word om die winste te bereken.

Die gebruik van liniêre modelle om ondersoek in te stel na die voorspelbaarheid van proefstukke blyk die norm in die meeste toetse van die doeltreffende mark-hipotesis te wees. Die tesis voer aan dat die wins-genererende proses nie noodwendig liniêr is nie, en indien dit die geval is, kan die nie-liniêre modelle die liniêre modelle in die proefstuk-voorspelling oortref. Die steekproef word as 'n betroubare beskrywing van die gedrag van aandelepryse beskou, maar net indien dit nie deur enige van die alternatiewe modelle in die voorspelling van aandelepryse in die proefstuk oortref word nie. Dit is empiries getoets deur die toepassing van die indeks-data van die Afrika-aandelemarkte in die proefstuk. Daar is bevind dat alternatiewe modelle in die meeste gevalle die ewekansige steekproef-model in proefstuk-voorspelling oortref.

Die ewekansige steekproef-resultate word deur die resultate van seisoenale patrone en ander afwykings van die doeltreffende mark-hipotesis gestaaf, soos die grootte van die onderneming en die invloede van prysinkomste. Grootte en prysinkomste-verhoudings is as betekenisvolle voorspellers van aandele-winste op ander markte geïdentifiseer. Daar is spesifiek aangedui dat die portfolios van klein maatskappye dié van groter maatskappye oortref en dat die portfolios van lae prysinkomste-maatskappye dié van hoë prysinkomste oortref. Die grootte en invloede van prysinkomste wat in die tesis bepaal is, is hoofsaaklik presies die teenoorgestelde van dié waaroor in die literatuur 'n hipotese oor opgestel is.

Die bestaan van seisoenale patrone weerspreek die stelling dat aandelepryse hulle op 'n lukrake wyse voordoen. Dié verskynsel is op Afrika-aandelemarkte ondersoek deur indeks-opbrengste te gebruik. Hierdie studie meet die bevindinge aan die hand van Suid-Afrika se Effekte Wisselkoerse op die Johannesburgse Aandelebeurs, ander opkomende markte soos Brasilië, Maleisië, Pole, Slovenië en Finland, en ontwikkelde markte soos die van die VSA, Australië en Nieu-Seeland. Seisoenale invloede word op sommige waargeneem, maar nie op alle aandelemarkte in Afrika nie - in die meeste gevalle verskil die patrone wat waargeneem is van dié op aandelemarkte elders.

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LIST OF ACRONYMS

ACF	Autocorrelation function
ACI	All companies index (Botswana)
ACIA	Africa Centre for Investment Analysis
ADF	Augmented Dicky-Fuller
ADR	American Depository Receipt
AMEX	American Stock Exchange
ANN	Artificial Neural network
ANOVA	Analysis of Variance
APT	Arbitrage Pricing Theory
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ASPGEN	skate Press Agency General Index
ATS	Automated Trading System
ATT	Adjusted trade-to-trade
BARC	Barclays Bank of Zimbabwe
BARDNET	An electronic database by Techfin Private Limited (Zimbabwe)
BBK	Barclays Bank of Kenya
BDS	Brock-Dechert-Scheinkman
BPN	Back Propagation Neural Networks
BRVM	Bourse Regionale des Valeurs Mobilieres (West Africa Regional Stock Exchange)
BRVM-C	Bourse Regionale des Valeurs Mobilieres – Composite Index
BVMT	Bourse des Valeurs Mobilieres de Tunis (Tunis Stock Exchange)
C/P	Cashflow-to-price ratio
CAC 40	Compagnie des Agents de Change 40 Index (for Paris Stock Exchange)
CAPM	Capital Asset Pricing Model
CASE	Cairo and Alexandria stock Exchanges

CDC	Commonwealth Development Corporation
CFG	Casablanca Finance Group
CFG 25	Casablanca Finance Group 25 Index
CMA	Common Monetary Area
CSCS	Central Securities Clearing System
CSE	Casablanca Stock Exchange
CSR	Cosumar (Mauritius)
DAX 30	Deutscher Aktienindex 30 (German Stock Exchange 30 Index)
DELT	Delta Corporation Zimbabwe
DJIA	Dow-Jones Industrial Average
DOW	Day-of-the-Week effect
DRC	Democratic Republic Of Congo
DSE	Dhaka Stock Exchange
DWHI	David Whitehead Industries
E/P	Earnings-to-price ratio
EFAR	Exponential Feedback Autoregressive model
EFGI	Egyptian Financial Group Index
EGCM	Egyptian Chemical Industrial
ELSG	El Nasr Clothes and Textiles company (Egypt)
EMH	Efficient Market Hypothesis
EMS	European Monetary System
ENT	'Entire' or normally calculated returns
EOM	End-of-month effect
EOY	End-of-year effect
EU	European Union
FACT	Form, accuracy, completeness and timeliness
FALG	Falcon Gold Zimbabwe
FCI	Foreign Industrial Index (Botswana)
FDI	Foreign Direct Investment
FNB	First National Bank
FPI	Foreign Portfolio Investment
FTSE 100	Financial Times Stock Exchange 100 Index
GARCH	Generalised Autoregressive Conditional Heteroscedasticity

GARCH-M	Generalised Autoregressive Conditional Heteroscedasticity-in-mean
GNP	Gross National Product
GSE	Ghana Stock Exchange
HFI	Hermes Financial Index (Egypt)
IFC	International Finance Corporation
IID	independent and identically distributed
INDUSTRIAL	Zimbabwe Industrial companies Index
INEG	Industrial Engineering Construction and Development Company (Egypt)
INID	independent normally and identically distributed
ISP	Internet Service Provider
IT	information technology
ITH	intergenerational transfers hypothesis
JB	Jaque-Bera
JET	Johannesburg Electronic Trading system
JSE	Johannesburg Stock Exchange
KOPSI 200	Korean Composite Stock Price Index 200
K-S	Kolmogorov-Smirnov test
LOCAL	Namibian Local Companies Index
LSE	London Stock Exchange
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCT	Multiple Comparison Test
ME	Market Equity
MGARCH-M	Momentum Generalised Autoregressive Conditional Heteroscedasticity-in-mean
MINING	Zimbabwe Mining Companies Index
MOY	Month-of-the-year
MSCI	Morgan Stanley Capital International
MTAR	Momentum Threshold Autoregressive model
NASDAQ	National Association of Securities Dealers Automated Quotations

NBDV	National Bank for Development (Egypt)
NBK	National Bank of Kenya
NICs	Newly Industrialised Countries
NN	Nearest neighbour
NRCD	National Redemption Council Decree
NSE	Nigerian Stock Exchange
NSX	Namibian Stock Exchange
NYSE	New York Stock Exchange
OTC	Over-the-Counter
OVERALL	Namibian Overall Companies Index
P/E	Price-to-Earnings
PACF	Partial Autoregressive Function
PFIZ	Pfizer Egypt
PHC	Plantations et Huileries de Cote d'Ivoire (BRVM)
PNDCL	Provisional National Defence Council Law
RBM	Reserve Bank of Malawi
RDC	RDC Properties
RMSE	Root Mean Square Error
ROW	Rest-of-the-Week
RTS index	Russian Trading System Index
RW	Random Walk
RWH	Random Walk Hypothesis
S&P	Standard & Poors
SADC	Southern Africa Development Community
SEC	Securities Exchange Commission
SEMDEX	Stock Exchange of Mauritius All Share Index
SEMTRI	Stock Exchange of Mauritius Total Return Index
SENS	Stock Exchange News Network
SETS	Stock Exchange Trading System
SGEN	Societe General Pour les (Egypt)
SLB	Sharpe-Lintner-Black model
SNN	Simultaneous Nearest Neighbour
STAR	Smooth Transition Autoregressive model
TA25	Tel-Aviv 25 Index

TOM	Turn-of-the-Month
TOT	trade-to-trade
TOY	Turn-of-the-Year
TSE 300	Toronto Stock Exchange 300 Composite Index
TUNINDEX	Tunis Stock Exchange Index
UK	United Kingdom
UMOEA	Union Monetaire et Economique Ouest Africaine (West African Economic and Monetary Union
US	United States
USA	United States of America
USB	University of Stellenbosch Business School
USB-ED	University of Stellenbosch Business School – Executive Department
WLS	Weighted Least Squares
WOM	Week-of-the-Month
ZPTF	Zambia Privatisation Trust Fund
ZSE	Zimbabwe Stock Exchange

1 INTRODUCTION

1.1 Background and synopsis

The efficient market hypothesis (EMH) suggests that a stock market is efficient if current market prices fully and instantaneously reflect all available information relevant to the valuation of the securities. The concept was first developed by Fama (1965, 1970), in reference to the theoretical contributions of Bachelier (1900)[1] that stock prices move randomly through time, and the fair game theory of Mandelbrot (1963)[2,3] who related stock price changes to the theoretical construct of fair game. The EMH also relates to the theory of asset pricing, which follows from the law of one price. This law requires that assets with the same payoffs must trade at the same price. The bottom line is that the price of the asset should be a true reflection of the asset's intrinsic value. If the price of the asset is equal to its intrinsic value, then it is correctly priced. For the market to be efficient, all securities must be correctly priced, that is, they must reflect all available information.

Despite the vast body of evidence on the efficiency of developed markets such as the United States and European securities markets (Groenewold and Ariff, 1998; Mobarek and Keasey, 2000), evidence from emerging markets, and in particular, the frontier markets of Africa, is still very scarce. This is so despite the fact that the latter have been the fastest growing share markets over the past decade. The few studies that have been undertaken on the African stock markets have generally provided a less favourable degree of support for the EMH in comparison to the evidence on the developed economies. The general perception is that African stock markets are the least efficient, in comparison to world markets, including relative to their Asian and Latin American counterparts.

The perception emanates from the general characteristics and operational inefficiencies of these stock markets, far divorced from those of stock markets in

[1] In Cootner (1964)

[2] The article was also published in Cootner (1964)

[3] See also Samuelson (1965)

other parts of the world. African stock markets are characterised by a lack of liquidity, thin trading, volatile returns and thus high risk, fewer institutional investors, and far more regulatory and institutional impediments in comparison to developed markets. These characteristics of African stock markets have resulted in the continent attracting less private equity investment from developed countries than Asia and Latin America, despite the rapid emergence of stock markets in the region over the past decade, increasing in number from only 7 in 1988 to 21 in 2004.

While the role of information has become more important with the growing globalisation of financial markets, stock markets in Africa have been sluggish in adopting the necessary information technology infrastructures. Information dissemination, and thus the medium used, is of paramount importance to efficient markets. Electronic information dissemination, through the Internet for example, makes stock price information accessible to a broader range of investors, beyond national boundaries. Although many African stock markets are migrating to electronic or computer-based trading systems, the pace is rather slow for most of these markets, with only a few exceptions such as the Johannesburg Stock Exchange (JSE), the Ghana Stock Exchange (GSE) and the Namibian Stock Exchange (NSX), among others. This move to electronic trading is made in an effort to make the exchanges "more relevant, more efficient and more effective" in the trading, clearing and settlement of deals, and also to enhance market transparency and efficiency.

As Mobarek and Keasey (2000) pointed out, the issue of market efficiency is important to security analysts and investors in their investment decisions and to security exchange regulatory bodies in their policy-making decisions aimed at improving market conditions. Balaban and Kunter (1996), in their study of the Turkey Stock Market, also pointed out that investors, both domestic and foreign, would benefit from empirical results on market efficiency. This would help them develop profitable trading strategies, since all information variables would be low-cost and readily accessible. A vast body of evidence, particularly from developed markets, supports the EMH, at least in the weak form. Even in the case of emerging markets, as pointed out by Singh (1992), a number of investigations of the EMH do not always reject the weak form of the hypothesis. According to Singh, one would not expect the

EMH to hold even in the weak form for third world markets, as they appear to be very imperfect.

The rapid emergence of stock markets in Africa tallies with most financial liberalisation programmes on the continent. Financial liberalisation is crudely defined as the creation of a free market environment whereby market forces influence the allocation of financial resources from those with excess funds to productive ventures in the economy. The stock market potentially plays that role, given that it is efficient. If stock prices reflect new information as it arrives in the market, then stock price changes would act as signals to savers and investors in constructing their investment portfolios. Firms would also be able to acquire and efficiently utilise funds in their production activities. Pricing in an efficient market, therefore, reflects the performance and risk of alternative investments. If the market were inefficient, the allocation of financial resources would be inefficient leading to inefficiency in production and monopoly profits. Stock market efficiency is, therefore, important in boosting investor confidence. It is also a necessary condition for the stock market to fulfil its developmental role and to ensure that equity funding is made available for a broad range of ventures.

The EMH, however, faces some challenges. The biggest challenge is the growing evidence on market efficiency anomalies, and in particular, the seasonal, firm size and price-earnings anomalies. The hypothesis is that excess returns can be obtained by exploiting these anomalies in investment decisions. Anomalies are defined as irregularities or inconsistencies that conflict with the whole idea that security prices behave in a random manner. The EMH is also not directly testable, but requires models of expected returns. Tests of market efficiency are, therefore, joint tests of the expected returns model and market efficiency. Thus rejection of this joint hypothesis could stem from either market inefficiency or the use of an incorrect expected returns model. Most of the models used to test the EMH are linear, justified by the EMH assumptions. However, researchers in emerging markets are becoming increasingly doubtful on the relevance of linear models in testing the EMH. This is because of the belief that stock prices are generated by chaotic dynamic systems, leading to nonlinear dependencies.

Most prior studies on market efficiency have included very little comparisons between markets, and between regions, and reference to Africa has been minimal. African stock markets, which also crudely fall under the emerging markets umbrella, are probably the least researched in finance studies. The few African countries included in emerging market studies are those that are relatively older, bigger or are performing better than others. Of interest have been stock markets such as the Johannesburg, Ghana, Nigeria, Egypt and Zimbabwe stock exchanges. The other markets have received relatively less coverage.

The objective of this research project is to investigate if African stock markets are weak form efficient. The thesis tries to answer the following questions:

- Are the perceptions that African stock markets are not efficient empirically justified?
- What implications does thin trading, a serious problem on these markets, have on the efficiency of the markets?
- Can the results from the study of individual markets be collectively generalised for Africa as an investment region?
- Are the anomalies (seasonal, firm-size, and price-earnings) that have been found on major stock markets also evident on the frontier African stock markets, and what deductions can one make about the efficiency of these markets from such anomalies?
- Is the efficiency of African stock markets relatively comparable to the efficiency of stock markets elsewhere?
- Which forecasting models give the best performance for African stock markets out-of-sample: linear or nonlinear?

1.2 Data

The greatest challenge to any research project on Africa is the scarcity and/or unavailability of data. In the event that one manages to obtain the data, its accuracy is not without doubt, which calls for a more cumbersome process of verifying, validating and discarding some or whole sets of data. The same problems were experienced during this study and data collection proved to be a lengthy process, as the objective is to use data with a high degree of accuracy.

A number of databases were consulted, including Reuters and DataStream. The other sources used were stockbrokers trading on the respective stock exchanges and the stock exchanges themselves. Since computerised and electronic trading was only recently introduced on some of the African markets with the rest still using the open-outcry and call-over systems, obtaining data predating as far back in history as required proved to be difficult. Even though the research was initially intended to cover a period of 10 years from 1992 to 2002 of daily data, the unavailability and inaccessibility of data has resulted in the period being limited to about 5 years from 1997 to 2002 for most markets. The other factors, which contributed to this reduction in the period of investigation, are that

- some of the markets had very few stocks listed in 1992 and there has been a number of suspensions of trade, new listings and de-listings during the period;
- the trading patterns of stocks have not been stable with some of the stocks becoming more infrequently traded over time (visual data inspection); and
- some of the markets were established later than 1992, in particular the West African Regional Exchange (Bourse Regionale des Valeurs Mobilieres - BRVM) in Cote d'Ivoire.

1.2.1 Company selection criteria

The inclusion of a company in the sample selected for each stock exchange was determined by the availability of data on that company and the following conditions:

- The company was listed throughout the period covered by this research, which was from January 1997 to May 2002 for about half of the markets. The periods covered for the other half of the markets were relatively shorter.
- The company did not merge with any other company during this period. If a company had merged with another and the merged company had listed under a different name, both the new company under the merger and the listed companies before the merger were excluded.
- The company was neither a product of nor subject to an acquisition, in which case the acquiring company, if it was already listed continued operating under

the same name, or if it was not listed, was listed on the local exchange as a new entity.

- The company did not have its trade suspended for more than 10 consecutive trading days during the period under review.
- At least 30 data points had to be available for each company analysed to ensure meaningful statistical analysis.
- The company's data was accurate beyond reasonable doubt.

The final samples of stocks selected for each market are shown in Appendix A.

1.3 Research outline

Chapter 1 provides the theoretical background to this study and elaborates on the data used. Chapter 2 reviews African stock markets, including their emergence, trading, and institutional and regulatory structures. The chapter is not limited to the stock markets covered in the empirical investigations of this thesis but gives an overall view of all the stock markets in Africa. This is to enable the reader to have a feel and deeper understanding of the markets in the region.

Chapter 3 presents the theory on the testing of market efficiency. Emphasis is placed on the random walk hypothesis. Tests of the random walk hypothesis have been used to test weak form efficiency. These tests include the serial correlation and runs tests. However, although the evidence supporting the random walk is sufficient to show that a market is weak form efficient, rejection of the random walk does not necessarily imply that the market is weak form inefficient. Further tests (which are not discussed in this chapter) would be required to determine whether the serial correlation observed can be exploited to generate abnormal profits, net of transaction costs. If abnormal profits can be generated, then the market is considered weak form inefficient.

In Chapter 4 the consequences of online information dissemination on stock market efficiency and liquidity are examined. For the EMH to hold, a medium of information dissemination and transaction ordering with both speed and accuracy is required. This chapter chronologically presents arguments in favour of the Internet as one such medium. The Internet has also enabled the transmission and archiving of bulky information in a ready-to-use format. Abnormal returns are now quickly observed and arbitraged away to non-existence. Correlation analysis is used to establish the relationship between the Internet (measured by the number of internet users) and some stock market development indicators.

Chapter 5 investigates the random walk behaviour of stock returns (defined as capital gains plus dividends) on four African stock markets for which dividend information was available. Worth noting is the way returns are calculated using the trade-to-trade approach and adjustments are made to account for interval variability. The adjustment is done by weighting each trade-to-trade return by the number of days between trades. A test is performed to find if this adjustment method is justifiable. The adjusted stock returns are also tested for normality. In testing if stock returns follow a random walk, two simple traditional testing methods, first used by Fama (1965), namely the serial correlation and the runs tests are used.

Chapter 6 is an extension of Chapter 5. The stock returns used in this chapter are capital gains only and excludes dividends. This is done in order to include the markets on which dividend information is not available. The evidence currently available on the African stock markets is based on the use of weekly and monthly indices data. However, even though such evidence is of considerable value, the approach is not without limitations. To adjust for thin trading, the trade-to-trade approach is used in calculating returns.

Chapter 7 investigates and presents empirical evidence on the severity of thin trading on African stock markets and its implications on market efficiency testing. The chapter also compares the following approaches to measuring returns that have been used in the literature: (1) entire series of returns disregarding the thin trading phenomenon; (2) trade-to-trade return series; and (3) adjusted trade-to-trade return series. Of the methods used, the trade-to-trade, and its variant, the adjusted trade-to-trade approach, are widely acclaimed measures of returns in thinly traded markets. The chapter also investigates autocorrelation in observed individual stock returns possibly attributable to nontrading.

Chapter 8 investigates the out-of-sample predictabilities of African stock market indices using both linear and nonlinear models, and compares it with the random walk model. An increasing amount of evidence suggests that stock markets lack orderliness and stock returns are thus generated by nonlinear dynamic systems. The linear models engraved in the theory of market efficiency are considered not very appropriate in emerging markets considering these markets' uniquely disordered microstructures.

Chapter 9 examines the relationship between stock returns and beta, size and the price-earnings ratios for those markets that have market capitalisation and price-earnings (P/E) ratios available. The positive relation between beta and average returns hypothesised in the literature is also investigated. In the literature African stock markets were found to exhibit characteristics that are different from those exhibited by stock markets elsewhere.

Chapter 10 investigates seasonal effects in sixteen indices on nine African stock markets using regression analysis and the Kruskal-Wallis and median tests. The more powerful Kruskal-Wallis test was used to investigate day-of-the-week and turn-of-the-year effects, turn-of-the-month and week-of-the-month effects, and month-of-the-year effects.

Chapter 11 gives evidence of seasonal effects on stock markets in countries used as benchmarks in this study. Although some seasonal effects exist on these markets, just as on the African stock markets, the patterns observed are not necessarily the same. This is taken to suggest that the factors explaining the existence of seasonal effects are more numerous and could be market specific, such that explanations given for some markets may not be applicable to African markets. Therefore, future research on seasonal effects on African stock markets should also focus on trying to find explanations as to why seasonal effects exist on these specific markets.

Chapter 12 summarises and concludes the thesis. It also highlights the limitations in this current study and identifies areas for further research.

1.4 Conclusion

With the recent emergence of stock markets in Africa, addressing the repellent factors to investment, such as the informational efficiency or inefficiency of these markets is very important. Most of these markets are still young and therefore have potential to grow. This study is valuable in that it provides empirical evidence on the efficiency of African stock markets. If investors avoid Africa, this should be justifiable on the basis of evidence and not merely perceptions.

2 A BACKGROUND ON AFRICAN STOCK MARKETS

2.1 Introduction

International investors have been showing an increasing interest in emerging markets. However, Asia and Latin America have attracted most of the investment community's attention, while Africa continues to lag behind. These are the same regions that have absorbed most of the equity flows from developed countries. The emerging markets of Asia have attracted almost all the private equity investment from Japan and half the equity dollars invested in developing countries by the United States in 1993 (IFC, 1997). Africa and the Middle East remain largely ignored, yet their economies represent 16 percent of all emerging markets (IFC, 1997). There must be an explanation for investors' preference for Asia and Latin America rather than Africa (and the Middle East). East European countries, formerly in the same category as African countries, have subsequently been categorised as 'Newly Industrialised Countries' (NICs), whilst African countries still occupy the bottom positions in economic development rankings.

Emerging markets are at the top of the list of the world's best performing stock markets. In 1996, they occupied the top 15 positions when evaluating annual performance measured in dollar terms from a list of 76 stock markets (IFC, 1997). The worst performers also happen to be concentrated in emerging markets. Of the 21 world equity markets that dropped in prices in 1996, 19 were emerging markets (IFC, 1997). Even though the International Finance Corporation (IFC) did not group these emerging markets according to regions, it is most likely that only a handful of African stock markets took the top positions, but made up the majority of the worst performers.

The increasing interest by private equity investors in developing markets is accredited to push and pull factors. The push factor is to obtain better profits and increased diversification because of the knowledge that returns in emerging markets are generally higher, even after adjustments for risk, than in mature markets (World Bank, 1995). Because of the low or even negative correlations between stock market returns in developing and in developed nations, investing in the developing world is considered a means to reduce overall portfolio risk (World Bank, 1995). The pull factor is a result of wide-ranging reforms, legislative as well as economic in many developing countries. Governments have liberalised or eliminated capital restrictions, improved the flow of financial information and strengthened investor protection thereby earning the attention of the investment community.

However, if there is any region that should feasibly benefit from these push and pull factors, it is Africa. African markets are characterised by high returns and lack of contagion with other emerging markets (Collins and Biekpe, 2001). Therefore, investing in Africa would be a good way to diversify one's investment portfolio. The pull factor should have been stronger, considering the fact that the late 1980s and early 1990s witnessed a number of financial liberalisation programmes in Africa. However, the problem in Africa is that financial liberalisation has been, in most cases, only partial, or a gradual process, and not fully implemented. According to Bekaert, *et al.* (2001), financial liberalisation is associated with significant increases in real economic growth, because it attracts the flow of capital into the economy. Ndung'u (2001) pointed out that the liberalisation of the foreign exchange market in Kenya resulted in short-term speculative capital flows responding to interest rate differentials. These capital flows were essentially portfolio flows for speculative purposes.

Ghana offered a number of investment legislative incentives in an effort to attract foreign investments. Asante (2000) highlighted some of these incentives. The first was the Pioneer and Companies Act of 1959, followed by the Capital Investment Act of 1963 (Act 172), both of which sought to encourage foreign investment. The 1973 Investment Decree (NRCD 141) and the Investment Policy Decree (NRCD 329) of 1975 encouraged both local and foreign investments. The 1981 Investment Code (Act 437) sought to centralise investment promotion functions at the Capital Investment Board and to consolidate all investment legislation. The 1985 Investment Code (PNDCL 116) established the Ghana Investment Centre as the Central Investment Promotion Agency.

Factors that have been deterrents to investment in Africa include the monetary, macroeconomic and fiscal policies. According to Asante (2000), the high interest rates on government financial papers together with the rudimentary state of the capital market, partly explains why private investment in Ghana has remained very low in spite of the abundant market reforms. He added that the distortions in the tax treatment of capital and investment income acted as disincentives to new investment and may have retarded the necessary restructuring of many private enterprises. He also referred to a fast depreciating exchange rate being a cause of concern to investors. According to Asante, macroeconomic policies can only boost private sector response if all components, such as the exchange rate, the debt burden, the parallel market premium, and the inflation rate are addressed simultaneously.

2.2 The role of the stock market

The heartbeat of an economy is the financial sector and its ability to mobilise savings for investment in the productive sectors of the economy. Osei (1998) and Engberg (1975) stressed that capital markets can significantly raise the level of domestic savings and contribute to a more efficient allocation of such savings among competing uses. The availability of a wider range of financial assets induces people to increase their rate of current savings. Competition among the users of capital market funds will tend to increase the efficiency with which the capital is used with direct effect on the growth rate of the economy. According to Pardy (1992), the demand and supply of securities is crucially linked to the state of the macro-economy. If the macro-economy is conducive to profitable business operations, a sufficient number of sound businesses can develop to a stage where access to securities markets is useful for their continued growth. If sufficient profitable businesses with good prospects for the future do not exist, there is little reason to have a securities market.

According to Levine (1990), the stock market accelerates economic growth (1) by facilitating the ability to trade ownership of firms without disrupting the productive processes occurring within firms, and (2) by allowing investors to hold diversified portfolios. However, the stock market can only perform its functions if it is developed. Demirguc-Kunt and Levine (1993) highlighted the characteristics of stock market development as:

1. Traditional: - which includes market capitalisation, the amount of new capital raised through stock offerings, the number of listed companies and turnover;
2. Institutional: - which includes the regulatory environment, information disclosure, transparency rules and trading costs; and
3. Asset pricing: - which includes the market efficiency and the degree of integration into world stock markets.

2.3 The emergence of African stock markets

Africa is the second largest continent after Asia with 54 independent countries of which 48 are mainland and 6 are island states and an estimated population of 700 million people. Of the 54 African countries, 21 have a national stock exchange. These are Algeria, Botswana, Egypt, Morocco, Ghana, South Africa, Sudan, Zambia, Malawi, Mozambique, Mauritius, Kenya, Namibia, Nigeria, Swaziland, Tanzania, Tunisia, Uganda, Zimbabwe, the Ivory Coast (Cote D'Ivoire) and recently Cameroon. Figure 2.1 below shows the geographical distribution of these stock markets.

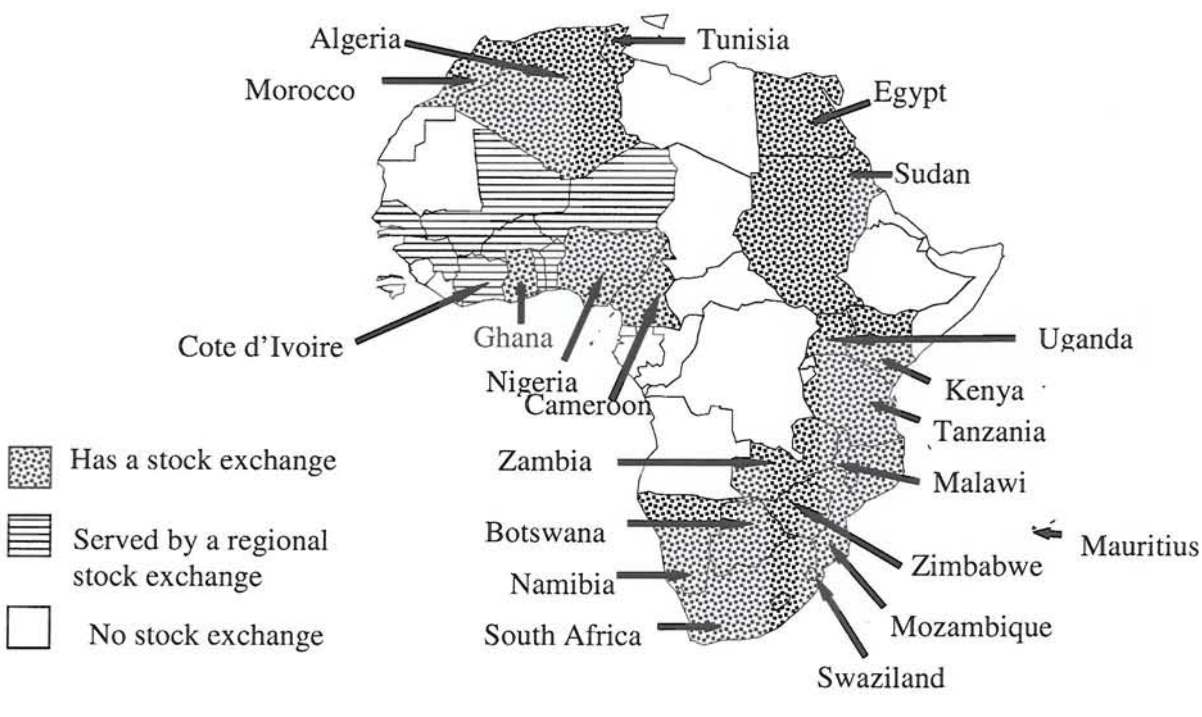

Figure 2.1: The geographical location of stock markets in Africa
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Most African stock markets emerged in the late 1980s and early 1990s, a period that witnessed a number of financial liberalisation programmes in the region (Bekaert and Harvey, 2001b). This emergence was mostly driven by the desire to privatise state-owned enterprises and thus integrate Africa into the global economy. In the Kenyan economy, the Nairobi Stock Exchange has been playing an important role in the privatisation of state-owned enterprises. The 10 years between 1988 and 1998 saw the privatisation of 9 public enterprises through the stock exchange. The stock exchange has also been used as a tool to empower the general public. For example, on the Lusaka Stock Exchange, the five public offerings up to 1999, under Zambia's privatisation programme, were open only to Zambians. The only instance in which shares were also offered to international investors was in 1996 when the Zambia Sugar Plc was listed. This was mainly because the shares on offer were a combination of those warehoused by the Zambian Privatisation Trust Fund (ZPTF) and those owned by the Commonwealth Development Corporation (CDC).

With the shift of interest from foreign direct investment (FDI) to foreign portfolio investment (FPI) (Mate, 2000), stock markets are increasingly gaining importance as attractors of foreign funds into the region and as tools for encouraging domestic savings. This is expected to filter through into the much-needed economic growth, which has been sluggish in the past, averaging 2.2 percent from 1978 to 1985, and 2.0 percent from 1986 to 1993 (Erb, *et al.,* 1996).

Most African stock markets were, and some still are, characterised by restrictive regulations, especially to foreign investors. Of major concern are the capital flow regulations, restricting the remittance of capital, capital gains, dividends, interest payments, returns and other related earnings thereby constraining foreign investment. Bekaert and Harvey (2001a) highlighted that financial liberalisation makes markets more attractive to foreign investors. Foreign investors would diversify their portfolios driving up local equity prices and reducing the cost of capital. This in turn would enhance stock market liquidity and thus accelerate economic growth. According to Bekaert and Harvey (2001a), Chile's liberalisation of equity markets and opening up to foreign investment in 1992, contributed to the economy's growth of 6.3 percent per year. Africa also awoke to the call for free market economies, with wide-ranging reforms, varying from legislative to economic, taking place on Africa's equity markets. While some restrictions should be eliminated under financial liberalisation, insider-trading laws need to be enforced in order to ensure a level playing field for all investors.

2.4 Foreign portfolio investment in Africa

The sudden emergence of stock markets in Africa in the 1990s raised a lot of interest from the investment community. However, most international investors still look at Africa as one investment block. The United Nations (2001) reported that some foreign portfolio investors shied away from the West African sub-region, as they perceived it to be politically and economically unstable. The main market indices of the BRVM in Cote d'Ivoire and the Ghana Stock Exchange fell by 15.8 percent and 32.9 percent respectively in US dollar terms in the first half of 2000 (United Nations, 2001). The events in the neighbouring countries of Sierra Leone and the Democratic Republic of Congo (DRC) impacted negatively on the performance of the Ghana Stock Exchange. The conclusion is that even events in neighbouring African countries impact on investor sentiments regarding a specific country.

Investors need assurance that situations such as the Mexican peso crisis and the Asian crisis will not be repeated in Africa. The financial crisis in Asia sent shock waves that had an impact on investment sentiment in some African countries. Despite being less directly exposed to unstable equity and financial markets, most African countries were hit by the mounting global economic crises, especially through shrinking markets for African commodities. South Africa, the largest economy on the African continent, was the only market directly affected. Investors, who were already on edge because of the Asian crisis, are said to have stampeded out of South Africa in May 1998 in response to the rumours about the dismissal of the Reserve Bank governor and an impending devaluation of the Rand, both of which were unfounded (United Nations, 2001). The Asian crisis sent one key message to African markets; that in the absence of efficient information flows, adequate regulation and market transparency, they are susceptible to high volatility and risk.

average. The other African stock markets are relatively small compared to the JSE and their emerging market counterparts in other regions. The exchanges are also small relative to their economies, with the market capitalisation of the Nigerian Stock Exchange only representing 8 percent of gross national product (GNP), while in the case of Zimbabwe, Kenya and Ghana, the market capitalisations range between 25 percent and 35 percent of GNP (Kenny and Moss, 1998). In terms of listed stocks, the JSE has the majority (70 percent) of listed stocks in the Southern African Development Community (SADC) region, followed by the Zimbabwe Stock Exchange (ZSE). Of the more than 2 000 firms listed on Africa's stock exchanges, the majority are listed on Egypt's Cairo and Alexandria Stock Exchanges (CASE) followed by the JSE. However, only a small percentage of stocks listed on the CASE are actively traded.

2.5.2 Regulatory environment

Some of the African stock markets were established on the back of poor regulatory and legislative frameworks. This, among other things, explains why some of these markets lack the capacity to deal with capital market dynamics. Legislations to prevent insider trading are either inadequate or non-existent and even in the presence of laws or regulations enforcement is often poor.

The successful integration of African markets into the world financial system requires regulatory frameworks that conform to international standards. An appropriate legal and regulatory framework, sufficiently monitored, is a necessity to protect investors and the integrity of the markets. It also helps to instil confidence, a sense of fairness and financial discipline in the market. In most countries the regulator is a government agency, the central bank, finance ministry or an independent commission. In some countries, the capital market is accorded regulatory powers to become a self-regulatory body, or the power to regulate is a shared responsibility between two or more agencies.

2.6 Institutional characteristics

2.6.1 Trading times

Table 2.2: Trading arrangements on African stock markets

Stock Exchange	Trading days	Trading hours	Trading method
Algeria			
Botswana	Mon to Fri	09h00 and 15h00 (call over times)	Open outcry system
Cameroon (Douala)	N/A	N/A	N/A
Cote d'Ivoire (Abidjan)	Closed	Closed	Closed
Cote d'Ivoire (BRVM)	Mon to Fri	10h45 to 12h00	Decentralised electronic fixing system
Egypt (Cairo & Alexandria)	Sun to Thurs	11h30 to 15h30	Electronic order-driven trading
Ghana	Mon, Wed, & Fri	10h00 to 13h00	Call-over with a limited auction
Kenya (Nairobi)	Mon to Fri	10h00 to 12h00	Open outcry system
Malawi (Blantyre)	Mon to Fri	09h00 to 12h00	Call-over system
Mauritius (Port Louis)	Mon to Fri (Official); Tues & Thurs (OTC)	10h00 to 11h00 (Official); 14h00 to 15h00 (OTC)	Open outcry, order-driven and single price auction system
Morocco (Casablanca)	Mon to Fri	08h30 to 12h30	Electronic order-driven (liquid stocks). Fixing basis (less liquid stocks)
Mozambique (Maputo)	-	-	-
Namibia	Mon to Fri	09h00 to 16h00 (summer) 08h00 to 15h00 (winter)	Computer-based JSE Equity Trading System (JET)
Nigeria	Mon to Fri	From 11h00 until all bids are done	Automated computer-based system
South Africa (Johannesburg)	Mon to Fri	09h00 to 16h00	Open outcry, continuous auction on a trading floor; order-driven
Sudan (Khartoum)			
Swaziland	Mon to Fri	10h00 to 12h00	Call-over system
Tanzania (Dar es Salaam)	Tue, Wed, Thurs	10h00 to 11h00	Open outcry auction system
Tunisia (Tunis)	Mon to Fri	08h00 to 11h00	
Uganda	Tue to Thurs	10h00 to 12h00	Open outcry auction system
Zambia (Lusaka)	Mon to Fri	10h00 to 11h00 (1st session) 12h00 to 13h00 (2nd session)	Single price auction
Zimbabwe	Mon to Fri	08h00 to 16h30	Call-over system

Sources: Stock exchange websites

The majority of stock markets in Africa trade daily, from Monday to Friday (Sunday to Thursday in Egypt), except Ghana, Tanzania, and Uganda, which trade three times a week. Ghana trades on Monday, Wednesday and Friday, while Tanzania and

Uganda trade on Tuesday, Wednesday and Thursday (see Table 2.2). Trading times also vary, ranging from one hour per trading day in Tanzania to the whole business day from 08h00 to 16h30 in Zimbabwe. This information is given in Table 2.2.

2.6.2 Trading systems

Trading methods on African stock exchanges vary from open-outcry to call-over to electronic trading systems. While a handful of markets have moved to electronic trading, many still use either the call-over or the open outcry systems (Table 2.2). The method of trading on a stock market significantly impacts on a stock market's trading activities and tends to boost investor confidence. The Nigerian stock market has replaced the call-over trading system with the automated trading system (ATS). Clearing, settlement and delivery of transactions on the exchange are now done electronically by the Central Securities Clearing System (CSCS), a subsidiary of the Stock Exchange.

Following the closure of the open-outcry trading floor in June 1996, the JSE introduced an order driven, centralised, automated trading system known as the JSE Equities Trading (JET) system. In May 2002 the JET system was converted to the Stock Exchange Trading Systems (SETS) used on the London Stock Exchange (LSE). SETS is a world-class, flexible and robust trading platform that promise improved liquidity and ensure more efficient functionality. SETS also allows South African based companies access to offshore privileges without having to move offshore. Other markets that adopted the SETS trading system include Ghana and Namibia Stock Exchanges.

Migration from an open outcry to an electronic trading system on the Casablanca Stock Exchange (CSE) took place between 4 March 1997 and 15 June 1998. All securities quoted on the CSE are now traded on the electronic trading system. Orders entered by dealers are automatically sorted by price limit and in chronological order, in the "market order book". On the central market, the less liquid securities are quoted on a call auction or fixing basis (once per session). The more liquid securities are quoted on a continuous basis. The electronic trading system automatically downloads to a market information system. This means that data providers can receive real-time market data (time, price, number of shares traded, etc), just as it appears on the dealers' screens.

2.6.3 Trading costs and foreign investment restrictions

The acquisition of shares by foreigners is limited on some African stock markets and they also face prohibitive institutional and tax barriers as shown in Table 2.3. These, together with other trading costs, act as disincentives to foreign portfolio investments.

Table 2.3: Foreign investment restrictions

Stock Exchange	Withholding taxes			Commission rates	Foreign Investment Ceilings	
	Interest	Dividends	Capital gains		Individual	Collectively
Algeria	-	-	-	-	-	-
Botswana	15%	15%	None	1% to 2%	5%	49%
Cameroon (Doula)	-	-	-	-	-	-
Cote d'Ivoire (Abidjan)	N/A	N/A	N/A	N/A	N/A	N/A
Cote d'Ivoire (BRVM)	-	-	-	-	-	-
Egypt (Cairo & Alexandria)	0.20%	-	2%	No fixed rates	No restrictions	
Ghana	10%	10%	None	1% to 2.5%	10%	74%
Kenya (Nairobi)	15%	10%	None	1.1% to 2%	5%	40%
Malawi (Blantyre)	15%	None	35%	1% to 2%	10%	49%
Mauritius (Port Louis)	None	None	None	0.9% to 1.25%	Open to foreign investors	
Morocco (Casablanca)	None	-	None	0.6%–0.3%	No restrictions	
Mozambique (Maputo)	-	-	-	-	-	-
Namibia	None	10%	None	0.35% to 1.1%	No restrictions	
Nigeria	10%	10%	None	1% to 2.75%	No restrictions	
South Africa (Johannesburg)	None		None	1.2%–0.2%	15% (banks), 25% (insurance companies)	
Sudan (Khartoum)	-	-	-	-	-	-
Swaziland	10%	15%	None	1% to 2%	None	
Tanzania (Dar es Salaam)	5%	5%	None	1.1% to 2%	Closed to foreign investors	
Tunisia (Tunis)	None	None	None		No restrictions	
Uganda	15%	15%	None	1.1% to 2%	No restrictions	
Zambia (Lusaka)	15%	15%	None	fixed 0.25%	No restrictions	
Zimbabwe	10%	15%	10%	1% to 2%	10%	40%

Source: Stock exchange websites

2.6.4 Restrictions on capital flows

Most stock markets in Africa operate in regulatory environments with stringent exchange controls on the remittance of investment capital, capital gains, dividends, interest payments, returns and other related earnings. In Malawi, for example, the Reserve Bank of Malawi (RBM) manages the exchange control. Foreign investment capital, whether in the form of equity or loans, needs to be registered with the RBM. Foreign loans and equity investments, the remittance of dividends and capital, among other transfers, require permission from the RBM. In the case of Mozambique, remittance of funds overseas is restricted. Foreign investors can remit loan repayments, dividends and capital if permission has been obtained for amounts above US$5 000. In Zimbabwe, dividend remittances in respect of projects approved by the Zimbabwe Investment Centre are allowed at 100 percent of after tax profits. Capital is blocked and may be remitted through 20-year 4 percent government bonds, denominated in Zimbabwean dollars. Capital is paid in 10 equal annual instalments at the end of years 11 to 20.

In some countries such as Botswana, Mauritius, Zambia and Uganda, there are no foreign exchange controls. Profits, dividends and capital can be freely repatriated. In Ghana, the financial regime is relatively flexible and allows the free transfer of foreign currency in and out of Ghana. A foreign investor may, subject to approval, operate a foreign currency account with banks in Ghana. In Kenya, the Foreign Investment Protection Act guarantees that foreign investors can convert and repatriate capital freely. The Exchange Control Act was repealed in 1995, removing the last of the restrictions on profit remittances and borrowing.

Namibia, as part of the Common Monetary Area (CMA) with South Africa, Swaziland and Lesotho, has unrestricted capital flows for non-residents. Capital, profits and dividends can be repatriated. Exchange control limitations do apply to resident capital flows. South Africa has adopted the approach of gradually abolishing exchange controls. Restrictions on non-resident capital flows were fully liberalised with the abolition of the financial Rand in 1995. Restrictions on residents are gradually being relaxed. In Swaziland, there are no foreign exchange restrictions between CMA members. However, exchange controls between CMA members and the rest of the world may not be less strict than those of South Africa.

In Tanzania, foreign exchange controls were removed through the Foreign Exchange Act of 1992. Capital transfers are however still subject to approval by the Bank of Tanzania. Profits and dividends can be fully repatriated.

In Nigeria, foreign investors are guaranteed unconditional transfer of their capital and profits. Importation or exportation of foreign exchange above US$5 000 is declared. A domiciliary account can be opened in foreign currency at banks and cash withdrawals from such accounts are permissible. For purposes of exchange control and monitoring the flow of foreign currencies, authorised dealers are required to inform the central bank whenever transfers larger than US$10 000 are made into a domiciliary account.

2.7 Operational characteristics

2.7.1 Liquidity and trading frequency

Despite the importance of liquidity to ensure that stock markets promote economic growth, African stock markets are illiquid and characterised by thin trading, in comparison to stock markets in other regions. According to Kenny and Moss (1998), 8 of the world's 12 most illiquid stock exchanges in 1995 were in Africa. None of the stock markets south of the Sahara had a turnover above 10 percent in 1995, compared to Turkey with 226 percent, China with 115 percent and the USA with 85 percent. Liquidity of equity markets, according to Levine (1996), makes investment less risky and more attractive. It facilitates longer-term, more profitable investments, thus improving the allocation of capital, which in turn enhances the prospects for long-term economic growth. Levine (1996) found liquidity to be a much better predictor of economic growth than stock market size and volatility.

2.7.2 Volatility, risk and returns

The macroeconomic and political environments in which African stock markets operate are less favourable for foreign portfolio investments. While foreign investors value solid macroeconomic policies and a stable regulatory framework (Bekaert and Harvey, 1997), African economies are characterised by foreign exchange risk, political risk, low liquidity and other informational and institutional barriers. The high political risk on the continent is evident in the civil wars, military coups and other political unrests, crime and violence that persist. Exchange rates, interest rates and inflation rates fluctuate in most African countries, creating an economic risk and prohibiting long-term investments. When interest rates are low and inflation is high, the money market becomes less favourable for investment, resulting in investors shifting their assets to the stock market. High interest rates (and inflation) were partly the cause of the small growth in the index of the Ghana Stock Exchange in 1995. In early 2001, the Reserve Bank of Zimbabwe published a new monetary policy and advocated for a reduction in interest rates. The Treasury bill rate fell to as low as 5 percent and rose slightly to range between 11 percent and 13 percent on 90-day Treasury bills.

Expected annual volatility is also, on average, high on the African markets. In Erb, *et al.* (1996), volatility was an average 35.6 percent on African markets compared to 21.4 percent for the Morgan Stanley Capital International (MSCI) developed equity markets, measured using the countries' risk ratings. Kenny and Moss (1998) suggested that this extreme volatility is a result of the small size nature, lack of liquidity and, often, unstable political and economic environments. The higher expected volatilities on the African stock markets, implying higher risk, however, also imply higher expected returns as compensation for the risk. Erb, *et al.* (1996) found the average expected return for Africa to be quite high at 18.4 percent. The ability of African markets to attract investors, despite the high risks, rests upon the relatively higher returns these markets give on investments.

2.7.3 Segmentation/integration

Emerging (African) markets lack integration with world equity markets and also with each other. Erb, *et al.* (1996) found the average correlation of African stock markets with world markets to be a low 0.05 percent. The segmentation of African markets implies that investors demand compensation in the form of higher expected returns for their risk exposure. In integrated capital markets, investors hold securities from many countries providing a natural hedge for country-specific events. In a segmented market, investors are local residents and foreign participation is limited (Bekaert and Harvey, 1997). These markets are also associated with higher costs of capital and they relate to local volatility and country factors such as currencies and interest rates (Pension Fund Indicators, 2001). Globally integrated markets, on the other hand, are larger, more liquid and volatile and are associated with lower cost of capital, improved credit ratings, real exchange rate appreciation and thus increased economic growth.

The segmentation of African stock markets is partly due to restrictions on foreign investments. As a result of this segmentation, African markets lack contagion with global emerging markets, thereby making them potentially good portfolio diversifiers. For instance, African markets, except the JSE, were not affected by the Asian crisis due to the lack of interdependence with other global emerging markets (Collins and Biekpe, 2001).

2.7.4 Achievements

One of the greatest achievements of Africa is to have some of the continent's stock exchanges ranked among the top performers of emerging markets. The Egyptian Stock Exchange was very active in the 1940s and ranked fifth in the world. Ghana was ranked the sixth best performing emerging stock market in 1993 with a capital appreciation of 116 percent and the best performing of all emerging stock markets in 1994 with an index growth of 124.3 percent. In 1996, Zimbabwe had an increase in market capitalisation of 165 percent, making it one of the star emerging markets. This was partly attributed to the listing of the Ashanti Goldfields Corporation following its takeover of Cluff Resources. The Lusaka Stock Exchange was also quoted a star performer in Africa in 1997, whilst the JSE competes globally.

Africa also boasts of the first regional stock exchange, Bourse Regionale des Valeurs Mobilieres (BRVM) in Cote d'Ivoire. The BRVM was established in September 1998 after the closure of the Abidjan Stock Exchange in December of the previous year. It serves the 8 French-speaking member countries of the West African Economic and Monetary Union (UMOEA), namely Benin, Burkina Faso, Cote d'Ivoire, Guinea Bissau, Mali, Niger, Senegal and Togo. Other regional exchanges have been under consideration for some time, with one planned for East Africa to serve countries such as Kenya, Tanzania and Uganda. An integrated real time network for the Southern African Development Community (SADC) stock exchanges is also expected to be up and running by the year 2006 (Tyandela and Biekpe, 2001). Stock exchanges in the SADC are already adopting the listing requirements of the JSE in preparation for this integrated network. The JSE is fully computerised and has offered to give technical assistance to other exchanges in the SADC.

2.7.5 Growth potential

African markets, among other emerging markets, have high growth potential. This explains the interest these markets are receiving and the huge capital flows into emerging markets. The high returns on the markets are an indicator of the many business opportunities still unexploited. These opportunities still exist because of historically restricted access to capital markets, poor technological endowment, policy mistakes and political instability and unfortunate legacies, which are being redressed. Though limited in resource mobilisation individually, collectively African stock markets have potential for significant growth. Most of them are still in their embryonic stages of development and thus they still have room for growth.

2.7.6 Information asymmetry

The absence of insider trading laws on African markets has enhanced the perception that these markets are not efficient. Information asymmetry is assumed to be much more prevalent in Africa than anywhere else. Information asymmetry in a stock market refers to the presence of different groups of traders, those with more information (e.g. insiders) and those with very little or no information at all (e.g. noise traders). Insiders are investors who either hold more than a certain percentage of outstanding shares of a corporation or are part of the firm's management or directorship. These investors are likely to have access to information on the internal state, dividend earnings and access to the financial statements of the company before they become available to the public. Insider trading is defined as profiting from the use of price sensitive information that has not been disclosed to the rest of the market and has been one of the problems historically faced by the JSE. South Africa is one of the countries in Africa with insider trading laws. However, no prosecution for insider trading has taken place in South Africa due to the inadequacy of the legislation and the existence of lax and unenforceable laws.

2.8 Conclusion

African stock markets increased in number from only seven in 1989 to twenty one in 2004, and are, therefore, relatively young with high potential for growth. The driver of this emergence has been, in most cases, the desire to privatise state-owned enterprises. The unfavourable characteristics and poor regulatory environments, in which these markets operate, however, undermine their growth potential. Unfavourable laws and regulations, foreign exchange controls and restrictions on share acquisitions by foreigners marked the regulatory environments.

Efforts are, however, being made to relax or eliminate investment restrictions in order to promote foreign portfolio investments thus improving the liquidity and efficiency of the markets. The current considerations include integrating the African stock markets and establishing regional stock exchanges. Such moves will promote cross-border listings and thus stimulate increased liquidity across markets. This in turn will increase the incentive to get information about firms and to improve corporate governance (Levine and Zervos, 1996). It will also ensure increased growth potential thus enhancing the stock market's role in economic growth. One factor delaying the adoption of regional stock exchanges in Africa is that national stock exchanges are regarded as symbols of national pride. This has unfortunately resulted in less cooperation in integrating the stock exchanges, yet the improved liquidity, efficiency and performance that comes with such integration is of great importance in attracting foreign portfolio investment.

3 THE EFFICIENT MARKET HYPOTHESIS: THEORETICAL FRAMEWORK AND LITERATURE REVIEW

3.1 Introduction

Since the research published by Fama (1965, 1970), the EMH has attracted substantial attention from both investors and academics and thus has occupied centre stage in finance theory. Though there are three different forms of efficiency in the economics and business literature, namely Pareto, operational and informational efficiency, market efficiency is taken to refer to the last one in combination with market rationality. According to the EMH, changes in stock prices are caused by the arrival of new information, which is incorporated into prices speedily and accurately. The arrival of new information is assumed to be unpredictable and random, in that neither the time of its coming nor its nature (whether it is good or bad) is known. Investment strategies pursued in order to outperform a broad-based stock market will not consistently produce superior or excess returns after adjusting for risk and transaction costs.

Stock price fluctuations can thus be seen as evidence that the new information that is arriving in the market is being incorporated into prices. The nature of such information can be determined by observing the direction of the price movements. Good or positive information is expected to push up the price and bad or negative information to pull it down. If all new information is incorporated into prices as it becomes available, then the price changes will also behave randomly and would be unpredictable. Prices that do not change can be regarded as a reflection that there is no new information coming into the market[1], otherwise it would be an indication that the market lacks the power to process and interpret new information as it arrives (evidence against efficiency). If all relevant information in valuing a security is

[1] Any news that does not result in a change in price does not have any information content

incorporated into the security's price, that price will be an unbiased estimator of the security's intrinsic value.

It is important to note, however, that not all price fluctuations are a reflection that 'relevant' information is being fully and correctly incorporated into prices. Some price fluctuations may be just speculative bubbles caused by trading activities that are based on perceptions and human emotions, and not tied to any economic or fundamental event that impacts on the value of the security. Since prices reflect investors' expectations, this noise will result into prices merely reflecting human optimism and pessimism.

3.1.1 Forms of market efficiency

The EMH is categorised into three forms based on the relevant information set. Fama (1970) subdivided the relevant information into three sets namely historical prices, public information and private information to determine the three forms of market efficiency, namely weak form, semi-strong form and strong form efficiencies, respectively. More than two decades later, Fama (1991) generalised these forms of market efficiency by redefining the tests as return predictability, event studies and tests for private information. The information set for return predictability was expanded to include other variables such as volumes, interest rates, inflation, dividend yields, earnings-to-price ratios and other term-structure variables, in addition to historical price information. Due to this generalisation of weak form efficiency, other testing methods have erupted to enable the inclusion of even newer variables in the information set for weak form efficiency.

Weak form efficiency of a stock market, as currently defined, refers to a case whereby the current price of the security reflects all the information on the past price movements and trading history of the security. In other words, future price changes cannot be predicted from their own past. Investors (technical analysts) cannot devise any investment strategy to yield abnormal profits basing on the analysis of past price or return patterns. It is not possible to earn an above-market risk-adjusted return basing on such information. If profits can be made, it is only by luck, and thus something that cannot be repeated.

Weak form efficiency is often tested in relation to the random walk hypothesis (RWH). This hypothesis says that the direction as well as the size of change in the price of a share is random and cannot be predicted from past information about the share prices. According to this hypothesis, prices always adjust instantaneously to take into account all available information. No individual analyst, therefore, has more information than the information that is already reflected in the security's price.

Traditionally, tests for weak form efficiency have been based upon two separate hypothesis of the random walk: (1) that successive price changes are independent and (2) that the price changes conform to some probability distributions (Fama, 1965). Basing on these 'hypotheses', past research has attempted to determine if stock prices over time have sufficient serial correlation or memory to allow investors to predict future price movements by studying trends and whether there are investment (trading) strategies based on price movements that can provide opportunities for abnormal profits.

Semi-strong efficiency asserts that security prices at all times fully reflect all public information. This information includes, but is not limited to, historical price and trading patterns, stock splits, changes in annual earnings, declared cash dividends, money supply, exchange rates, and interest rates and changes in the management of the firm, among other fundamental events. Such information is incorporated into stock prices immediately or the moment it becomes available such that it is not possible to make abnormal profits basing on such information. This form of efficiency renders fundamental analysis fruitless in that no investment strategy based on analysing annual reports and past dividends, for example, can generate abnormal profits.

The test for this form of efficiency has come to be known as 'event studies'. It involves studying price reactions to the announcement of events that impact on the value of the security (Levy and Sarnat, 1984). In an efficient market, the information should be incorporated into stock prices the moment it is announced. If it is possible to exploit this information and obtain an excess return, the market is said to be semi-strong inefficient.

In its strong form, a market is said to be efficient if security prices reflect all information, whether it is publicly available or only known to insiders[2] (private). No painstaking analysis of the company will result in successful investment managers who can consistently beat the market. Not even the insiders can achieve this goal. Surely this cannot be true considering that markets are far from being perfect. This is also reflected in the enactment of insider trading laws by most countries, because the possibility of insiders making superior profits while acting on inside information is very high. This form of efficiency has not been as widely tested as the other two as the perception is that markets are not efficient in the strong form, and due to data constraints.

Strong form efficiency tests involve the studying of the performance of professional money managers such as mutual funds or insiders. Insiders are likely to have access to information on the internal state, dividend earnings and access to the financial statements of the company before they become available to the public. The study of insiders tends to give more conclusive results than the study of mutual funds. This is because if mutual funds earn excessive returns, it could be due to other factors and does not necessarily mean that they possess private information. If insiders make excess returns and the outsiders who follow insider transactions do not, the market is said to be semi-strong efficient but inefficient in the strong form.

In the announcement of earnings, for example, the general opinion among practitioners has been that stocks with low price-to-earnings (P/E) ratios yield higher returns than those with high P/E ratios. Before the earnings information is announced, it is considered private. An investor who wants to follow the recommendation to invest in low P/E stocks will not be able to make his investment decision until such information is made public. The investor will not earn excess profits if the market is semi-strong efficient, because by the time the information is made public it is worthless. Only the insiders who may have access to earnings information before it is made public can make excess profits by investing in low P/E stocks.

3.1.2 EMH assumptions

The validity of the EMH is based on a number of fundamental assumptions. One of these assumptions is that there are a large number of sophisticated traders all competing amongst themselves to try and locate mispriced stocks and to locate bargains in their buying and selling of shares. In an efficient market bargains would not exist and investors' buying or selling decisions would not have any economic value other than the true value of the security. The competition among traders will drive the security price towards its fair or intrinsic value and thus ensure market efficiency

The word 'sophisticated', used by Fama (1965) to describe some market traders, qualify investors or analysts with the ability and special skills to interpret specific information as it arrives in the market, and who can respond to such information with speed and accuracy. The literature refers particularly to two types of traders, intrinsic value analysts (fundamentalists) and superior chart readers (technicians). These two groups of traders differ in their sophistication, but the presence of both in large numbers and their different approaches in analysing information is important to ensure that the market is efficient. Depending on the level of their sophistication and the low correlation in their mistakes, their individual errors tend to average out and the security's market price will be a better, unbiased estimate of its intrinsic value.

The EMH also assumes that investors have homogenous and rational expectations. However, due to information asymmetry, a characteristic of most markets, the assumption of homogenous expectations is rather too strong. This has led to the general belief that markets are not necessarily efficient in the strong form. Information

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[2] Insiders are investors who either hold more than a certain percentage of outstanding shares of a corporation or are part of the firm's management or directorship. In the USA, the SEC defines insiders as members of the board, corporate officers, shareholders holding more than 10% of equity, etc. Such individuals are required to disclose any change in their monthly stock holdings.

asymmetry in a stock market refers to the presence of different groups of traders, with one group, insiders in particular, holding more information than the rest of the market. On the other extreme are those who trade on no information at all, usually referred to as noise traders.

However, it is not possible for a market to be completely free of noise traders, those who act upon feeling and human emotions. These investors tend to have expectations that reflect their hopes, moods and fears and would act upon such noise as if it were information and in some cases may demand risky assets not justified by fundamentals (they are irrational). According to Fama (1965), noise tends to produce bubbles in the price series whereby the price would run well above or below the intrinsic value of the security. The presence of many sophisticated traders, who through their analysis can determine when the price has gone above/below its intrinsic value and whose rational behaviour would tell them to sell short/buy, would neutralise or cause the bubbles to burst. Thus if all traders have homogenous and rational expectations as the EMH assumes, a security's price would at all times be equal to its intrinsic value and mispriced stocks would be difficult to identify and exploit. That means the market would be efficient. The deviation of prices from their intrinsic values is therefore a reflection that there are some traders who are not acting rationally and the fact that these bubbles burst before they really get underway is a sign that there are also some rational investors in the same market. The market will thus be characterised by heterogeneously behaved investors.

The EMH in the strong sense assumes a perfectly competitive market with no barriers to entry and no restrictions on trading. Information is assumed to be available to all market participants at no cost. No tax asymmetries or costs in the execution of all transactions exist in such a market. The financial assets are assumed to be infinitely divisible and each market participant is sufficiently small and thus cannot affect prices by his or her own actions (all are price takers).

All these assumptions are far divorced from the real situation on the stock markets, especially the African stock markets. For example, assuming that there are no transaction costs is obviously not true because investors incur stockbrokerage fees and commissions, transfer fees, stamp duties and taxes in the execution of their transactions. The assumption of no restrictions to entry is also not true in some markets. For example, in Zimbabwe and Kenya there are foreign investment ceilings, whereby in Zimbabwe an individual foreign investor can only own up to 10 percent of a company's shares and collectively foreign investors can only own up to 40 percent of a company's shareholding. The assumption of infinite divisibility is again far-fetched as shares on most markets are sold in lots. The fact that most, if not all, of the strong form assumptions are not true in today's markets can be an explanation as to why market efficiency in the strong sense is less believable.

In an efficient market, it is also assumed that there are no arbitrage opportunities where arbitrage refers to the buying of an asset in one market and selling it at a higher price in another market. As soon as one is discovered, competition amongst the arbitrageurs will eliminate it. Arbitrage differs from speculation in that with the former the asset is bought and sold immediately whilst with the latter, the asset is held for sometime in anticipation of future price increases. Speculation involves risk since it is based on imperfect information. Arbitrage depends on the assumption of no barriers to entry since the requirement is that the arbitrageurs have access to the markets where the price differentials exist.

3.1.3 Anomalies

Challenging the EMH are some discovered irregularities or inconsistencies that conflict with the whole concept that security prices behave in a random manner. These irregularities are known as market efficiency anomalies. The most popular of these are seasonal anomalies such as the weekend/Monday effect, day-of-the-week effect, holiday effect, January effect, month-of-the-year effect, end-of-the-month effect and turn-of-the-year effect, among others. For example, there has been consistent evidence that returns on Mondays are more negative and significant than returns on any other day of the week. Another common finding in the empirical literature has been that stock market returns are, on average, higher in January than during the remaining eleven months of the year. Also attracting attention because of its link to the January effect is the firm size anomaly. The common finding has been that average returns of small firms exceed those of large firms and this is particularly evident in January.

3.2 The martingale and random walk hypothesis

The random walk hypothesis (RWH) has played a pivotal role in testing the weak form of the EMH since its inception in the 1960s even though the former predates the latter. The random walk has been found to describe best the behaviour of stock prices in an efficient market. Though most empirical studies have concluded on the weak form efficiency of a given stock market by testing the RWH, the scenario differs if the test results in the rejection of the random walk. This is because rejection of the RWH does not necessarily imply inefficiency of the stock market. Milionis and Moschos (2000) explained that where a constant expected return model is used, the RWH would be a joint test of weak form market efficiency and constancy of expected returns. Therefore, the RWH can be rejected not because the market is weak form inefficient, but because expected returns are not constant. In this case rejecting the random walk is as far as the researcher can go and cannot refute weak form efficiency based on such a rejection.

Contrary to the theory of random walks is the chartist theory, which has also been used in trying to explain the extent to which past prices can be used to make meaningful predictions concerning the future price of a stock. Chartist theories assume that the past behaviour of a security is rich in information concerning its future behaviour and that patterns can be identified, which can be exploited to increase expected gains. This theory has given rise to another body of testing methods known as technical trading rules and learning models, more of which are being discovered everyday.

Despite the fact that weak form efficiency cannot be rejected on rejection of the RWH, it does not nullify the usefulness of the random walk models in testing this form of market efficiency. The RWH has made it easier for researchers and academics to empirically test weak form efficiency by taking the random walk model as the stochastic process underlying price movements. The random walk and the martingales fall in the class of 'fair game' models.

The theory of random walks states that successive price changes are independent, identically distributed random variables, with not enough memory to be used to predict future price changes. Most researchers using statistical methods have tested the hypothesis of independency in which the probability distribution of price changes in the current period is independent of the sequence of price changes during previous time periods. The rationale of using the random walk in describing stock price behaviour, as in the Bachelier-Osborne proposition, is based mainly on the independence and unpredictable nature of new information across time and its random arrival in the market. Any dependencies that might exist, in either the information or noise generating process, would be offset by some mechanisms in the market, such as the presence of sophisticated traders, mentioned earlier, whose actions have a tendency of driving prices towards their intrinsic values and making the price changes independent.

3.2.1 Probability distribution hypothesis

The other sub-hypothesis of the random walk relates to the probability distribution of price changes. Fama (1965) pointed out the differing interests of investors and academics in this 'distribution' hypothesis. To the investor, knowing the distribution of price changes would help in determining the risk of investing in a particular stock while to the academic researcher it provides descriptive information concerning the nature of the process generating price changes, which is of great importance in statistical testing methods.

The strong form of the random walk in the Bachelier-Osborne model as reviewed by Fama (1965), assumes fairly uniformly spread transactions over time with a finite variance distribution of price changes. The price changes are assumed to be sums of many independent random variables, which under the central limit theorem is a description of the normal or Gaussian distribution. The variances of the distributions are assumed to be proportional to their respective time intervals such that the variance for the distribution of weekly changes, for example, should be approximately five times the variance for the distribution of daily changes. The variance ratio test of Lo and MacKinlay (1988) is most likely based on this theoretical construct.

The normal/Gaussian distribution was not disputed up until Mandelbrot (1962) observed some leptokurtosis in the empirical distributions of price changes and accorded them a more general class of distributions, the stable Paretian distributions. According to Fama (1965), stable Paretian distribution has two important properties, namely, stability or invariance under addition and a possible limiting nature for sums of independent and identically distributed (IID) random variables. This means that it has the same form as the distributions of the individual summands, except for origin and scale. The stable Paretian distributions are a broader class of distributions that allow infinite variances and in which the normal distribution falls as a special case.

In adopting these distributions in the formulation of the EMH, Fama (1965) first tested them using a sample of 30 stocks of the Dow Jones Industrial Average. He found that extreme tail areas were longer and contained more relative frequency than would be expected under the normal distribution. Some degree of leptokurtosis was also evident for all the stocks with the distributions more peaked in the centre than under the normal distribution. The evidence was thus in support of the stable Paretian distribution with characteristic exponents close to 2 (as expected under the normal distribution), but nevertheless less than 2 as asserted by the Mandelbrot hypothesis. This departure from normality could not be accorded to either a mixture of distributions between price changes or to non-stationarity (shift in mean) in the empirical results, although these are considered as possibilities.

3.2.2 A closer look at the 'fair game' models

3.2.2.1 The martingale model

In gambling, a fair game is one where, given equal conditions, none of the players expect anything other than their contribution to the game, or their initial wealth. The player's fortune received from the game is not affected by the history of previous plays. Whether the player has won or lost in the previous games, or whether there has been some dependence in the previous outcomes, does not help to increase his expected future winnings - the outcome will still be by chance. Whatever outcomes one get from previous games does not change the probabilities of outcomes in the next game, the expected gain would still be zero. This theory of a fair game is the foundation of the martingale hypothesis, which states that the best forecast of tomorrow's price is simply today's price or alternatively that the asset's expected price change is zero when conditioned on the asset's price history. The martingale model is expressed as follows:

$$E[P_{t+1} / P_t, P_{t-1}, \ldots] = P_t \tag{3.1}$$

or

$$E[P_{t+1} - P_t / P_t, P_{t-1}, \ldots] = 0 \tag{3.2}$$

where P_t is the asset price at time t.

Campbell, *et al.* (1997) assert that one other aspect of the martingale hypothesis is that non-overlapping price changes are uncorrelated at all leads and lags, thus rendering forecasting techniques for future price changes based on historical prices alone ineffective. According to these authors, the martingale was long considered a necessary condition for an efficient asset market in which the information contained in past prices is immediately, fully and continuously reflected in the asset's current price. However, the martingale hypothesis as it is, does not account for risk, such that positive returns might be the reward for bearing the risk associated with the asset. With proper adjustments for risk in asset returns, the martingale hypothesis can still hold.

Why would one want to play in a game and not expect a positive return for the effort and time that one puts into it? Why would one be willing to tie up one's capital by investing in an asset if there is no compensation for foregone alternative opportunities and the risk incurred in doing so? The martingale is thus not a perfect description of reality, which calls for its generalisation to accommodate expected non-zero returns. These generalisations come in the form of the super- and sub-martingales. The super-martingale is however, even more unrealistic as it puts a zero-return ceiling on expected returns. The sub-martingale provides a better explanation for the above gambling paradoxes. Under the sub-martingale models, equations (3.1) and (3.2) are satisfied by the following inequalities:

$$E[P_{t+1}/P_t, P_{t-1},...] \geq P_t \tag{3.3}$$

or

$$E[P_{t+1} - P_t/P_t, P_{t-1},...] \geq 0 \tag{3.4}$$

In the above cases, risk is accounted for in that investors expect a compensation for incurring the risk of investing in any particular stock. Under the sub-martingale, the serial correlation of returns need not be zero, but only the residual terms or deviations of the expected from the observed returns.

3.2.2.2 The random walk model

The random walk, as the underlying stochastic process or description of stock price behaviour, is a hypothesis that has gone through one or two insignificant changes. Initially, Bachelier (1900) assumed the probability distribution of price changes to have independent increments and to follow a normal/Gaussian distribution. With the Mandelbrot hypothesis, however, normality is not a necessary condition for the random walk to hold, although it simplifies things.

The random walk models are classified into three based on the assumptions. The strongest case is the random walk 1 (RW1), which assumes independent and identically distributed (IID) increments (ε_t) with a mean of 0 and a variance of σ^2. The model is specified as follows:

$$P_t = \mu + P_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim \text{IID}(0, \sigma^2) \tag{3.5}$$

where μ is the expected price change or drift. This model implies a fair game, but in a much stronger sense than the martingale. Assuming normality in the distribution of increments, that is, $\varepsilon_t \sim$ IID N(0, σ^2), will result in a model equivalent to an arithmetic Brownian motion. However, introducing normality violates limited liability and there will be a positive probability of having a negative asset price ($P_t < 0$), which is not possible in reality. To avoid this problem, the assumption of normally distributed increments is, instead, used on the natural logarithms of prices, $p_t = \ln(P_t)$ giving the following formulation:

$$p_t = \mu + p_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim \text{IID N}(0, \sigma^2) \tag{3.6}$$

This implies that continuously compounded returns are IID normal with mean μ and variance σ^2.

The weaker case to RW1 is random walk 2 (RW2), which assumes that price increments are independent but *not* identically distributed (INID). In other words, RW2 relaxes the assumption of homogeneous increments in RW1 to accommodate for other more general price processes. It allows for unconditional heteroscedasticity in the increments, a very important feature given that the volatility of many financial asset returns are time varying. RW2 contains the RW1 as a special case.

The weakest of the random walk hypotheses is random walk 3 (RW3). It relaxes the assumption of independence in RW2 and therefore assumes that price increments are neither independent nor identically distributed (dependent but uncorrelated increments) conditioned as follows:

$$Cov(\varepsilon_t, \varepsilon_{t-k}) = 0 \text{ for all } k \neq 0 \qquad \text{(uncorrelated returns)} \tag{3.7}$$

$$Cov(\varepsilon_t^2, \varepsilon_{t-k}^2) \neq 0 \text{ for all } k \neq 0 \qquad \text{(not independent)} \tag{3.8}$$

RW3 contains RW1 and RW2 as special cases and is the most widely tested hypothesis empirically. Applicable to all the three cases, a random walk is assumed non-stationary. Its conditional mean and variance are both linear in time as follows:

$$E[P_t/P_0] = P_0 + \mu t \tag{3.9}$$

$$Var[P_t/P_0] = \sigma^2 t \tag{3.10}$$

where P_0 is the initial price.

3.2.3 The random walk tests

Some of the well-known tests for the random walk, as pointed out by Campbell, *et al.* (1997), include non-parametric tests such as the Spearman rank correlation test, Spearman's foot rule test and the Kendall τ correlation test; and parametric tests such as the likelihood ratio statistic, the canonical correlation and eigenvalues of the co-variances. In between the two are the semi-parametric tests, which require slightly stronger assumptions than the non-parametric tests on the joint and marginal distribution functions of the data-generating process.

Other more recent tests of the RW1 (tests for IID) include the Cowles-Jones ratio and runs test. The Cowles-Jones ratio consists of a comparison of the frequency of sequences and reversals, where sequences (reversals) are pairs of consecutive returns with the same (opposite) signs. The runs test, as defined by Campbell, *et al.* (1997), tabulates and compares the number of sequences of positive and negative returns, or runs, against its sampling distribution under the random walk hypothesis.

Test of the RW2 (tests of independence) include the filter rules and technical analysis approaches. Using the filter rule, an asset is purchased when its price increases by x percent and sold when its price drops by x percent to create a long or short position respectively. Technical analysis is based on the belief that historical price series, trading volume and other market statistics exhibit patterns or regularities that can be exploited profitably. Autocorrelation coefficients and variance ratios are normally used as tests for the RW3. Other tests of the random walk include the Box-Pierce Q-statistic and unit root tests.

3.3 Prior evidence

3.3.1 Empirical evidence on African stock market efficiency

Evidence on the efficiency of African stock markets is very scarce. The majority of studies have been conducted on the JSE (e.g. Bhana, 1995/96, 1998, 1999; Gilbertson and Roux, 1977, 1978; High and Honikman, 1995/96; Knight and Aflleck-Graves, 1983; Okeahalam and Jefferis, 1999; Philpott and Firer, 1994/95; Strebel, 1977, 1978; etc) with only a few individual studies on other selected African markets. Most of the studies on other African stock markets are unpublished theses that have been done in fulfilment of Masters and Doctoral degrees and little is known about them (e.g. Chiwira, 2001; Kiweu, 1991). The majority of African studies have focussed on the weak form of the EMH. The popular method has been to test if stock prices or returns follow a random walk using the autocorrelation coefficients and runs tests.

Kiweu (1991) used these two tests on the Nairobi Stock Exchange for the period January 1986 to December 1990 in a sample of 10 blue chip companies in terms of market capitalisation. With the autocorrelation test, he used lags 1 to 5, and 12 and 24. The autocorrelation test supported the random walk, whilst in the case of the runs test, 8 out of 10 runs were greater than expected, indicating negative correlation. However, using the 2-tail significance test at the 5% level, the random behaviour in price changes could not be ruled out in 9 out of the 10 companies. The conclusion was that the Nairobi Stock Exchange is weak form efficient.

Chiwira (2001) used the random walk model to examine the weak form efficiency of the Zimbabwe Stock Exchange (ZSE) by employing the Augmented Dickey-Fuller test for unit roots. He used monthly stock price data for a 5-year period, 1995 to 1999, in a sample of 20 stocks. His null hypothesis, that stock prices follow a random walk, could not be rejected at the 1% level of significance. This led to the conclusion that the ZSE is weak form efficient.

Using the autocorrelation test and the Box-Pierce (1970) Q-statistic for lags 1 to 10, Olowe (1999) tested the weak form efficiency of the Nigerian Stock Exchange. He used stock returns data of 59 securities for the period January 1981 to December

1992. He claimed his test results to be in line with those of Ayadi (1983) and Samuels and Yacout (1981), that the Nigerian Stock Market is weak form efficient.

Bundoo (2000) also used the autocorrelation test for up to 8 lags in a sample of 9 companies out of the 19 listed on Port Louis Stock Exchange in Mauritius as at January 1992. He found the market to be inefficient in the weak form showing strong positive correlation in returns. However, he hinted that the results be interpreted with caution as they might also be evidence of time-varying risk premiums or the infrequent trading of shares (thin trading).

Asal (2000) pointed out that autocorrelation and random walk tests are incapable of capturing nonlinearities such that the failure of prices to follow the random walk may reflect thin trading and illiquidity rather than inefficiency. This was one of the views held by Strebel (1977) in his critical evaluation of the results of Gilbertson and Roux (1977) supporting efficiency on the JSE. The presence of transaction costs may also force market participants to respond to information that arrives in the market with a lag.

There has been a shift of interest to evolving/changing informational efficiency in which case the GARCH-in-mean approach is used and the sampling period is sub-divided on a yearly basis or according to regime changes. In order to measure changing efficiency, Asal (2000) tested the efficiency of the Egyptian Stock Exchange on a yearly basis, arguing that this will capture the impact of changes in the institutional and regulatory framework on market efficiency. The results showed that the market was inefficient from 1992 to 1996, with the inefficiency manifesting itself through nonlinear behaviour, and became efficient in 1997.

Smith and Jefferis (2002), similarly, investigated the evolving efficiency of seven African stock markets, namely, South Africa, Egypt, Morocco, Nigeria, Zimbabwe, Mauritius and Kenya. They used the GARCH approach after being motivated by the presence of heteroscedasticity and risk in these markets. They argued that tests of the random walk hypothesis (RWH) such as the Lo and MacKinlay (1988) variance-ratio test could not readily capture changing efficiency. Smith, *et al.* (2000) tested the weak form efficiency of these markets using the Chow and Denning (1993) multiple variance ratio test, in which only the South African market's stock price index exhibited a random walk and was thus considered weak form efficient. In the test for evolving efficiency (Smith and Jefferis, 2002), the JSE was found to be weak form efficient throughout the whole period, while Egypt and Morocco became weak form efficient from 1999 and Nigeria from December 2000. Kenya and Zimbabwe showed no tendency towards efficiency and Mauritius a very slow tendency.

The pioneers in the evolving efficiency tests and in the use of the GARCH-in-mean approach were Emerson, *et al.* (1997) in testing the weak form efficiency of the thinly traded Bulgarian stock market. Hall, *et al.* (1998) used the same approach in testing changing market efficiency of the Russian stock market using two indices, the RTS index of the most liquid stocks and the ASPGEN index comprising a wider number of stocks. Berg (2000) also used a similar approach on the Swedish stock market using daily data in which he concluded that the Swedish stock market seemed to become more and more informationally efficient, at least in the weak form in the 1990s when compared to the 1980s.

A comparative analysis on the efficiency of African stock markets with other emerging markets is of great importance. This is because of the general perception that among the emerging markets, African stock markets are the least efficient, if efficient at all, such that investors abscond Africa and channel their investments to Asia and Latin America instead. Empirical evidence has, however, shown this to be unfounded. Magnusson and Wydick (2002), for example, tested the efficiency of 8 African stock markets making comparisons with 9 Latin American and Asian markets. The test results supported the weakest of the random walk hypothesis, the random walk 3, in 5 of the 8 African markets, that is, Botswana, Cote d'Ivoire, Kenya, Mauritius and South Africa, and rejected it at the 95% confidence level in Ghana, Nigeria and Zimbabwe when returns were measured in nominal terms. Interestingly enough and against general perception, only 3 of the 9 Asian and Latin American markets in their sample (i.e. South Korea, Taiwan and Ecuador) conformed to RW3 in nominal terms.

Measuring returns in US dollars, the test results remained the same for all the markets except Nigeria in Africa and Brazil and Argentina in Latin America, which shifted from rejecting RW3 to conforming to it. The six African markets that conformed to RW3 were further tested for RW2 and all except Botswana passed this second test. In the case of Latin America and Asia, only two markets, Ecuador and Brazil, conformed to this second test. However, none of the markets conformed to RW1 except the US market, which was used as a benchmark.

3.3.2 Evidence from the Johannesburg Stock Exchange

There is a fair amount of evidence on the efficiency of the JSE, although conflicting in some cases. Gilbertson and Roux (1977) reviewed the evidence for and against the efficiency of the JSE using statistical methods, trading rules and portfolio performance tests. They argued that even though they found small deviations from independence using the statistical (serial correlations and runs tests) methods, this was no justification for rejection of the EMH. Their basis for argument was that tests for independence are in fact tests of the random walk model rather than the EMH. Statistical tests, they argued, also suffer from the problem of non-stationarity and non-normality of price changes and some are too unsophisticated to identify complex nonlinear patterns in share prices. Using an evaluation of the trading rules, the buy and hold strategy was found to consistently outperform the trading rule strategy thus supporting the EMH. The portfolio performance tests were also consistent with the EMH thus resulting in the conclusion that the JSE is weak form efficient.

Strebel (1977) disputed the results obtained by Gilbertson and Roux (1977) with the suggestion that the efficiency of the JSE is a half-truth considering that half of its shares are thinly traded. He used an intuitive discussion to differentiate the RWH from the EMH. He pointed out that with the RWH, the change in a share's price during any period is in no way dependent on previous price changes, whilst with the EMH, the expected return rather than the whole distribution of returns, is independent of previous returns and equal to the equilibrium value anticipated by the market.

In defence of their results, Gilbertson and Roux (1978) argued that Strebel erroneously assumed that leptokurtic distributions imply non-random behaviour. They also claimed that they corrected for zero returns resulting from nontrading by omitting nontrading days from the calculation of returns. After re-examining their results using the same tests and taking into account Strebel's criticisms, they reached the same conclusion as before that the JSE is an efficient market. Strebel (1978) further critically evaluated this new evidence indicating that there was very little new in it and insisted that the efficiency of the JSE was rather "a half-truth".

High and Honikman (1995/96), using the serial correlation tests, the runs tests and the filter rule, concluded that the South African gilt market was weak form efficient for the period 30 March 1992 to 29 March 1993.

Philpott and Firer (1994/95) used share price anomalies to test the semi-strong form efficiency of the JSE. They defined the share price anomaly as a situation whereby there is significant deviation from the exact theoretical relationship between two related shares. The data analysis detected non-isolated price anomalies for many (82 percent) but not all of the pairs of shares in their sample. There were no anomalies in 4 of the 60 pairs and isolated anomalies were observed for at least two successive days in the other 49 pairs. Basing on the assumptions used, Philpott and Firer concluded that the JSE is not purely an efficient market. They also identified the liquidity ratio, value ratio code and shareholder activity as the 3 factors likely to influence market efficiency measured by the extent of share price anomalies.

Bhana (1995/96) examined the response of investors on the JSE to share prices of listed companies reporting positive or negative earnings (the overreaction to earnings hypothesis) during the fifteen-year period 1975 to 1989. He used a random sample of 200 companies reporting negative earnings and 200 companies reporting positive earnings. He based his study on DeBondt and Thaler (1987) who argued that the overreaction hypothesis is an exploitable market inefficiency. Bhana (1995/96) claimed his results to be consistent with those reported by Bhana (1989/90) and Page and Way (1992/93) supporting the overreaction hypothesis.

Bhana (1995/96) further investigated whether what appears to be a negative earnings effect is not actually a small-firm effect. The motivation for doing this came from

Zarowin (1989), who, contrary to De Bondt and Thaler, concluded that the overreaction phenomenon is in fact a size effect. However, Bhana's findings could not support Zarowin's conclusion. He found that the negative earnings effect exists independently of the small-firm effect. In comparing the overreaction to negative earnings of first time offenders versus repeat offenders, Bhana (1995/96) found that even though a strategy for buying first time losers may be profitable, even greater profits can be attained through predicting corporate recoveries of repeat offenders. Bhana concluded that investors either underestimate the degree to which earnings recover after a negative earnings year, or the market simply overreacts to negative earnings announcements or both.

In a similar study, Bhana (1998) investigated the share price reaction to special (extra) dividends announcements on the JSE for the period 1975 to 1994. He estimated the model using 40 daily returns, an estimation window of 43 days before the announcement to 4 days before the announcement. The results were consistent with the hypotheses that the announcement of special dividends results in an upward revaluation of share prices. The infrequent declarations of the special dividends were found to convey more information than those that appear on a more regular basis. He also found that share price reactions are negatively related to dividend declaration frequencies.

3.3.3 Evidence from emerging markets outside Africa

The majority of evidence on efficiency in emerging markets is from Asia and Latin America. Shachmurove, *et al.* (2001) used technical trading rules to examine the weak-form efficiency of the emerging market of Israel by analysing the Tel-Aviv 25 Index (TA25) and compared the results to the performance of the S&P 500. Yylmaz (2001) applied the variance-ratio-based multiple comparison test (MCT) to weekly and daily returns for 21 emerging stock markets over the period 1988 to 2000 to test the random walk (weak form market efficiency) in moving sub-sample windows. Tests on both weekly and daily return series indicated a move towards market efficiency over time.

Laurence, *et al.* (1997) tested the efficiency of the two Chinese stock markets, Shanghai and Shenzen, and found the market for "A" shares to be weak form efficient but not the market for "B" shares. Barnes and Ma (2001) found evidence to partly reject the semi-strong form efficiency of these two Chinese markets using the stock price reaction to the announcement of bonus issues. The 'A-shares' and 'B-shares' prices exhibited some similarities in their reactions to the approval of bonus issues. In their efficiency tests on the same markets, Darrat and Zhong (2000) found, in contrast to the variance-ratio test, the model comparison approach quite decisive in rejecting the random-walk hypothesis in both stock markets. Darrat and Zhong's results also strongly supported the Artificial Neural Network (ANN) as a potentially useful device for predicting stock prices in emerging markets.

In testing the weak and semi-strong form efficiencies of Singapore, Malaysia and Indonesia stock markets, Chye and Kendall (1996) used the unit root and co-integration tests. Their results showed that Singapore and Malaysia are fairly efficient in the risk-return trade off compared to Indonesia and that these markets are on the path to greater efficiency although less so for Indonesia and Singapore. Mobarek and Keasey (2000) used non-parametric tests (Kolmogrov –Smirnov normality test and the runs test) and parametric tests (autocorrelation test, auto-regression, ARIMA model) to investigate the weak-form efficiency of the Dhaka Stock Exchange (DSE). They used daily price indices of all the listed securities for the period 1988 to 1997. The results provided evidence that the share return series do not follow the random walk model and that the market is not weak form efficient.

Lee (1997) investigated the informational efficiency of the stock markets of the Pacific Basin countries of Hong Kong, Singapore, South Korea, and Taiwan with respect to macroeconomic policies using the Granger causality test in the context of a Vector Error Correction Model. The findings indicated that the stock markets of all the four countries are not efficient with respect to the two macroeconomic policies investigated, that is, money supply and the budget deficit (or surplus). Balaban and Kunter (1996) also used the direct Granger-causality test to investigate the semi-strong form efficiency of the financial markets of Turkey (the stock market, foreign exchange market and interbank money market). They found significant deviations from the EMH with respect to changes in market liquidity in all the markets for the period January 1989 to July 1995.

Otchere and Chan (1999) examined the short run overreaction hypothesis on the Hong Kong Stock Exchange using data from March 1996 to June 1998 and found evidence of overreaction in the pre-crisis period. The abnormal profits obtained from exploiting such a phenomenon were economically insignificant after taking into account transaction costs. Their conclusion was that the Hong Kong stock market is efficient in the weak form. On the Istanbul Securities Exchange, Balaban (1995) found no support for either weak form or semi-strong form efficiency in terms of the Composite Index for the period January 1988 to August 1994. In testing the efficiency of the Indian capital markets, the regression results found by Agarwal (2000) also failed to support the random walk model of market efficiency.

Del Brio, *et al.* (2001) investigated the profitability and information content of insider trading in the Spanish stock market. Their results showed that insiders earn excess profits when investing on corporate non-public information, while outsiders mimicking the insiders fail to obtain positive excess returns. Gu and Hitt (2001) used a model of financial market inefficiency to show, among other things, that the increase in uninformed individuals that result from a decline in transactions costs could increase market risk (volatility). Testing the predictions of their model, using data on the retail equities market, their results suggested that securities that have a large proportion of small trades tend to be less efficient by conventional measures, consistent with their model predictions.

3.4 Equilibrium models of normal returns

Models of normal returns are categorised into statistical, for example the market model and economic, such as the Capital Asset Pricing Model (CAPM). The models are of great significance in event studies (tests for semi-strong efficiency).

3.4.1 The market model

The market model has stood the test of time. The conventional assumption is that asset returns are jointly multivariate normal and independently and identically distributed through time. This assumption is sufficient for the model to be correctly specified and permits the development of exact finite-sample distributional results for the estimators and statistics. According to Campbell, *et al.* (1997), inferences using normal return models are robust to deviations from the assumptions, which can be explicitly accommodated using a generalised method of moments framework.

The market model relates asset returns in period t (R_{it}) to the market return in the same period (R_{mt}) using a linear specification that follows from the joint normality of asset returns as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}, \qquad E(\varepsilon_{it}) = 0, \qquad Var(\varepsilon_{it}) = \sigma^2_{\varepsilon i} \tag{3.11}$$

The variance of the abnormal returns is greatly reduced by removing the portion of the return related to variation in the market's return.

3.4.2 The capital asset pricing model (CAPM)

The CAPM, first developed by Markowitz (1959) and modified by Sharpe (1964) and Lintner (1965), implies that the expected return of an asset must be linearly related to the covariance of its return with the return on the market portfolio. The CAPM is a one period cross-sectional model based on the assumptions that investors are risk-taking expected utility maximisers with homogeneous (identical) expectations about future returns. It assumes that the market portfolio is mean-variance efficient and that borrowing and lending rates are equal (the risk-free rate). The capital market is assumed to be in equilibrium and there are no market imperfections such as taxes, regulations, transaction and information costs, or restrictions on short selling. The model can be specified as follows:

$$E(R_i) = R_f + [E(R_m) - R_f]\beta_i \tag{3.12}$$

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} \tag{3.13}$$

where R_i is the return on the asset, R_f is the return on the risk-free asset and R_m is the market return. Alternatively the model can be expressed in terms of excess returns on the asset, $Z_i \equiv R_i - R_f$ and excess returns on the market portfolio, $Z_m \equiv R_m - R_f$ as follows:

$$E(Z_i) = \beta_i E(Z_m) \tag{3.14}$$

$$\beta_i = \frac{Cov(Z_i, Z_m)}{Var(Z_m)} \tag{3.15}$$

Black (1972) derived a more general version of the CAPM where the expected return on an asset in excess of the zero-beta return is linearly related to beta specified as follows:

$$E(R_i) = E(R_{0m}) + \beta_i [E(R_m) - E(R_{0m})] \tag{3.16}$$

where R_{0m} is the return on the zero-beta portfolio, that is, a minimum-variance portfolio uncorrelated with the market portfolio. The Black model generally makes use of real or inflation-adjusted returns and can be tested as a restriction on the real-return market model specified as follows:

$$E(R_i) = \alpha_i + \beta_i E(R_m) \tag{3.17}$$

where the restriction is

$$\alpha_i = E(R_{0m})[(1 - \beta_i)] \tag{3.18}$$

The econometric analysis of the Sharpe-Lintner excess return version and the Black version of the CAPM is based on the assumption that returns are IID through time and jointly multivariate normal. Beta is usually estimated using the ordinary least squares (OLS) as the slope coefficient in the excess-return market model:

$$Z_{it} = \alpha_i + \beta_i Z_{mt} + \varepsilon_{it} \qquad (3.19)$$

where Z_{it} and Z_{mt} are realised excess returns for asset i and the market portfolio, respectively.

3.4.3 A review of studies on equilibrium models of normal returns

The market model and the CAPM have suffered great criticism and other models have come into existence as challenges to these models. A good example is the arbitrage pricing theory (APT). The APT is a multifactor model that includes other factors in the market model in addition to the market indices. Barone-Adesi, *et al.* (2000) proposed a two-factor model for asset pricing that, in addition to the traditional market return term, includes also the square of the market return to account for risk originating from co-skewness with the market portfolio. The quadratic term was able to account for heterogeneities across portfolios and was significant to such an extent that they concluded that the homogeneity hypothesis is accepted only in the presence of this term.

Sharma (2001) investigated the existence of heterogeneous expectations in the U.S. financial markets and their effect on stock prices. They found that for a blue chip stock like Ford Motor Company, the heterogeneous model is at least as good as the conventional EMH model. For the S&P500 Index, however, the heterogeneous model was found to outperform the homogeneous rational expectations model, a clear rejection of the EMH.

Driven by the critique of the CAPM by Roll (1977), and Fama and French's (1992, 1993) that it could not be validated by empirical work, Leusner, *et al.* (1996) presented a new empirical approach to estimating the CAPM. They took into account the differences between observable and expected returns for risky assets and for the market portfolio of all traded assets, inherent nonlinearities and the effects of excluded variables. They managed to provide evidence that the CAPM was 'alive and well'.

Hodson and Vorkink (2001) developed a semi-parametric efficient estimation procedure for the parameters of multivariate GARCH-in-mean models when the disturbances have a distribution that is assumed to be elliptically symmetric but is otherwise unrestricted. They claimed that their framework can be used to estimate and test conditional asset pricing models such as the conditional CAPM. Brailsford and Faff (1997) tested the conditional CAPM with the GARCH-M model using 16 years of daily Australian equity market data. The tests provided some support for the GARCH-M specification but with empirical limitation due to the inability of the 'in-mean' parameter to achieve statistical significance. The conditional CAPM was greatly supported for weekly return data supporting the notion that the asset pricing tests are sensitive to the return interval.

Otrok, *et al.* (2001) used recent statistical tests based on a distance between the model and the Hansen-Jagannathan bound, to compute the rejection rates of true models. They showed that the maximal-type-I-error critical values are appropriate for both time and state non-separable preferences and that they yield acceptably small type II error rates. Avramov (2000) investigated the restriction on stock return predictability imposed by asset-pricing models based on rational time-varying expected returns and equity characteristics. The results were found to carry implications for inference in long horizon event studies, evaluating equity mutual funds, and other applications using risk factors or equity characteristics as benchmarks.

Groenewold and Fraser (2000) compared standard test results with those obtained from procedures that do not require IID-normality. Analysing conditional and unconditional asset pricing models, they found that the use of tests that consider departures from the IID-assumption affect probability values, sometimes by a considerable amount. The results also suggested that issues surrounding the testing of joint hypothesis, influence probability values and that the use of appropriate tests may be more important when analysing US data than when analysing UK data.

3.5 Conclusion

Most empirical studies investigate the weak form efficiency of a given stock market by testing the random walk hypothesis. However, rejection of the random walk hypothesis does not necessarily mean inefficiency of the stock market. The EMH is rejected if the abnormal returns turn out to be predictable. The models of normal returns, the market model and the CAPM have also come under criticism but they have managed to stand the test of time.

4 INFORMATION DISSEMINATION AND MARKET EFFICIENCY[1]

4.1 Introduction

Market efficiency, as defined by Fama (1970), depends on the '*speed* 'and '*accuracy'* with which '*information'* is incorporated into prices. The speed requires the fastest medium of information dissemination that makes the information available in the market immediately and promptly to all stakeholders concerned. The past century has seen an eruption of such media with significant improvement in speed since the establishment of the first stock market in the 18th century. Before the advent of the internet, stock prices on different markets would respond to information with lags of days' length. Now it is only a matter of minutes, if not seconds to get market information across the world. This has made it easier to observe when a stock's price deviates from its intrinsic value and thus arbitraging away any abnormal gains. As Professor Goetzmann of Yale School of Management put it:

"By *the 18th century, financial news travelled fast -- in Rothschild's case it may have travelled by carrier pigeon. Studies of the efficiency of stock prices in this era indicate that when prices moved on the Amsterdam Stock Exchange on Monday, by Thursday they would move on the London Stock Exchange -- this is about the time it took for a fast messenger to travel the distance from city to city crossing the English Channel.*" (Online quote)[2]

In the early development of stock markets, traders were local enterprises and individuals, meaning that investors were confined to their locality. Slowly with the improvements in communications, starting with the telegraph and telephone, these markets transferred from being local markets to national markets. With further developments of the international telegraphic communications from the mid-19th

[1] This chapter is based on a paper presented by the author at the 5th World Wide Web Applications Conference September 2003

industries has been creating new forms of information and technologies that are used to compile and disseminate it.

Clarke and Rollo (2001) contributed to the definition of information by providing a distinction between data, information and knowledge. They defined data as sets of discrete objective facts, presented without judgement or context. Data is said to become information when it is categorised, analysed, summarised and placed in context, becoming intelligible to the recipient or user. Information, on the other hand, is data endowed with relevance and purpose. Information develops into knowledge when it is used to make comparisons, assess consequences, establish connections and engage in dialogue. Knowledge can be seen as information that comes with insights, framed experience, intuition, judgement and values, and it becomes wisdom when put to best use.

In financial markets, news reports are either in data form, information, knowledge or any combination of the three. Data in financial markets usually refers to statistics such as prices, volumes and number of trades, and is usually bulky. Without proper analysis, it is not easily intelligible or useful in decision-making. Research and investment analysts' reports can be said to provide information under the Clarke and Rollo (2001) definition. With inclusion of stock valuations and recommendations to buy, hold or sell specific stocks, these reports can be passed on as knowledge.

Freiden, *et al.* (1998) highlighted qualities of information, which they described as 'FACT', that is, Form, Accuracy, Completeness, and Timeliness. *Form* relates to the mode or medium through which the information is made available. An online information service is of little use to potential customers who lack access to the Internet. *Accuracy* describes how well the information represents the phenomena it purports to describe. Information that is inaccurate is misinformation and can be misleading or harmful to information consumers. *Completeness* refers to how much of the target phenomenon is described by the information available. Incomplete information may be useless to consumers or may have only reduced value. *Timeliness* refers to how up-to-date or current the information is. Outdated information is obsolete and may be of little or no value. It may in fact be misinformation and may mislead users. The importance of these qualities is nowhere better placed than in financial markets.

4.3 Online information dissemination

There are basically four different types of participants in the information market: the producers of the information, the brokers, value-adders and consumers (Yuen, *et al.*, 2001). For a financial information market, investors are the major consumers. While information is neither used up nor changed through consumption, it can become outdated with time. One other unique feature of information is that it can be consumed at a distance from its production site and can be distributed through several channels such as word of mouth, an ordinary store or mail order, dedicated phone lines and appropriate hardware such as the Internet.

Though a large part of published business information is available in printed form, databases are becoming increasingly important (Siriginidi, 1996). In the current era of information technology, also known as the Digital Information Age, it is almost the norm that information is stored and disseminated electronically. Traditionally, financial information/data was disseminated through traditional media or channels. Yuen, *et al.* (2001) remarked that at one time in the USA, financial filings were only made available to the public via five nationwide Securities Exchange Commission (SEC) reading rooms. In order to obtain the information they needed, investors had to travel to these locations, do a search and make photocopies. Private companies that also provided financial information via dedicated connections were charging extremely high prices. Although real-time financial information became readily available on a real-time basis, not every investor could afford it.

The age of information technology (IT) has brought with it the fastest medium of information dissemination with the capacity to handle large volumes of information and this medium is the Internet. With IT, statistical data and most financial information have been digitised and are much easier to handle and disseminate through the Internet despite the large volumes. According to Kamel and Hussein (2001), the Internet and the formulation of information highways have led to the development of the global information society that is driven by information dissemination and knowledge acquisition and management. Freiden, *et al.* (1998) also argued that as the world enters the information age, all types of digital data have become more important to many aspects of business, and selling, transporting and manipulating information has become a huge business.

The bulk of financial data is disseminated through the Internet in the hope that it will be widely available and useful to users (Yuen, *et al.,* 2001). When information is disseminated online, there is very little lag in the time with which it arrives in the market. The only time lag will be the time difference with which investors log on and surf on the Internet. Professional and institutional investors, however, usually stay connected for the whole time that the stock exchanges are open. These investors immediately act upon almost all the information that comes into the market. Most other small investors have their portfolios managed by Mutual Funds. The Fund Managers also keep track of the different shares and try to get first hand information, and in most cases they do this through the online information media. Without a speedy transmission of information, prices would not reflect the information immediately and markets would not be efficient.

4.4 Online trading

Market efficiency is not just about the speed with which information comes into the market but also the speed with which it is incorporated into prices. Incorporation involves investors' trading activities and the Internet has greatly improved this. Investors now have access to the fastest medium that enables them not just to acquire the information but also to execute transactions promptly, efficiently and at their convenience. Unsal and Movassaghi (2001) argued that the Internet has essentially allowed the ordinary investor more autonomy and flexibility in participating and influencing the market.

The appeal of online investing, as noted by Unsal and Movassaghi (2001), is the reduced transaction costs, convenience, speed and ease of use, and sense of control of one's own decisions that the online investor enjoys. Online trading enables investors to place their orders even after normal working/stock market trading hours and thus offer unlimited trade time. The Internet has enabled investors to access more reports and charts from more than one broker. In addition, investors can now search for the best broker for their needs with lower costs and reliability of service without going from one broker's office to another. The increased competition, low transaction costs and free information that comes with online trading promotes market efficiency. According to Unsal (2001, p58) "the playing field has become more level than before between the small investor and the Wall Street pros" when it comes to investment research and analysis on the Web.

Before investors can efficiently trade online on any market, it is a prerequisite that the market has electronic trading and settlement systems in place. Electronic trading and settlement promote the efficient operation of the stock market and improve its efficiency and liquidity through automated matching of buyers and sellers. Kadapakkam (2000) found that the introduction of the electronic settlement system on the Hong Kong Stock Exchange resulted in lower costs for arbitrageurs by reducing their minimum holding period for trades around ex-dividend days. Kadapakkam also found that the consequent reduction in risk exposure lowered the costs faced by arbitrageurs and enabled them to actively exploit positive ex-day returns. The switch to electronic settlement on the Hong Kong Stock Exchange led to an immediate drop in ex-day abnormal returns due to increased arbitrageurs actively eliminating excess returns in high-dividend-yield stocks. The finding was that with electronic settlement, the market never lacks trading volume. Kadapakkam observed that there was actually an increase in volume both before and after the ex-day in comparison to the period of physical settlement.

4.5 Advantages and disadvantages of the online media in financial markets

4.5.1 Advantages

There are several qualities of the online media that have made it more relevant in financial markets compared to other communication and information media. Financial analysts deal with bulky qualitative and quantitative information in their daily trading activities and decision-making processes. The timeliness and reliability of the information provided is of the essence. However, providing timely relevant information to investors that enables them to make informed decisions is a challenge. Even though the telephone, when compared to the print media, is a fast communication tool, it is less desirable in comparison to the Internet when it comes to the dissemination of financial information. A brief illustration is used to highlight the desirable qualities of the Internet in the dissemination of financial information and transaction-ordering in comparison to the telephone media.

The strengths of the Internet are as follows:

a) *It can be used for disseminating bulky information.* Bulky information is what characterises information in financial markets.
b) *It is time and cost efficient.* One can simultaneously reach all the investors by uploading the information on the Internet, yet with the telephone, to reach a million investors, one has to dial a million plus times.
c) *All investors will have accurate information at a particular point in time.* Information is avaliable to all investors as uploaded on the Internet. On the contrary, with the telephone, some investors will get the information through rumours as it *leaks* from those who already have it. The word "leak" means that such information will only be a certain percentage of the full information. This "leaked" information, upon which some investors will act, will not be full and accurate as required by market efficiency.
d) *It will reduce the chances of overreaction and/or under-reaction to stock market-related information.* This is because some overreaction and/or under-reaction could be a result of investors acting on inaccurate or incomplete information. Acting on inaccurate or incomplete information is more likely with the telephone when some reactions are based on rumours. Those who would have acted upon the rumours would tend to readjust their actions. At first they tend to overreact or under-react through speculation, causing irrational adjustments in prices. The second reaction would occur when accurate information is received (that is, from a reliable source) at which time these investors correct their positions and in so doing influence the prices. Assuming that the only dissemination media are the telephone and print

media, each investor will only have accurate information through either of the two. Even if investors would want to confirm the rumours with the source before they act, call congestion would result in many investors eventually giving up, out of frustration. Instead of waiting to confirm the rumours or to receive accurate information, most investors will act on the rumours as if it were information with the intention of readjusting if and when the rumours proved to be incomplete or inaccurate. Can the stock market be efficient in such an environment?

e) *It narrows the chance for insider trading and monopoly over information.* The information disseminated over the phone comes into the market with a lag, that is, not all investors would have accurate information at the same point in time. The first person receiving accurate information (i.e. the first person to be called) will have monopoly over that information and will tend to act upon it before the whole market does. This monopoly will dissipate from one person to the next in the chronological order in which they get the information. The stock price will only fully reflect the information when the last market participant gets the full/accurate information, at which time the participant is assumed to act[3]. This gradual incorporation of information into prices is evidence against the strong form of market efficiency.

The overreaction, underreaction and lagged response that can be associated with the telephone as described above can be illustrated diagrammatically as in Figure 4.1. The diagram shows that before the new information, the stock was trading at price P_0. The information content of the news will cause the price to immediately jump to P_n if the market is efficient. However, in the absence of a medium that ensures that all investors receive the news as accurate and timely information, the price might not necessarily jump as indicated by (a) in the diagram. Inaccurate or incomplete information may result in responses such as (b) or (c) or a sluggish response such as (d). Response (d) may also be a reflection of the time lag with which investors get and respond to the information. The Internet, on the other hand, seems to provide information with 'FACT', that is, *form*, *accuracy*, *completeness* and *timeliness* much more than the other media.

[3] This action might be a readjustment to an initial action based on rumours.

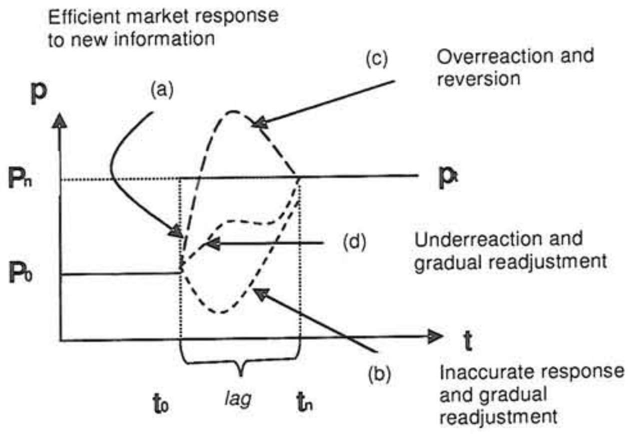

Figure 4.1: Market response to information
Source: Chipo Mlambo (2003) , University of Stellenbosch Business School

4.5.2 Disadvantages

The Internet has opened doors to rapid and abundant releases of information. According to Yuen, *et al.* (2001), huge amounts of financial data and information are generated daily and the number of websites providing such information on the Internet has increased very rapidly, creating the problem of information overload. This overload of information on the Internet has been further exacerbated by the quality of such information. This has caused the Internet to be termed an 'information jungle' by some people. It, therefore, requires skill to sift through this jungle for the relevant information. The reduced quality of information has made it difficult for users, especially the inexperienced investors, to determine and interpret the relevance and reliability of the information. Searching, retrieving and utilising financial data has become a major challenge to both users and researchers.

In a survey by Yuen, *et al.* (2001) on the usage of financial information on the Internet, the respondents indicated that financial information on the Internet is time consuming to gather; volatile to "catch"; poorly distributed and fragmented in nature; bulky to store; too fast to collect; easily perishable; not unique; varying in content representation and format; and difficult to be processed by humans. Availability of information has now ceased to be the major problem but the ability of the market to interpret such information has become a major concern. Yuen, *et al.* (2001) indicated, however, that different countries have developed different electronic financial filing systems to make it more web-accessible to investors. An ideal electronic filing system is one that allows the submission of documents via the Internet to increase the speed of transmission as well as to lower transmission costs, among other things. Such an electronic financial filing system, according to Yuen, *et al.* (2001), would increase the transparency and efficiency of markets and would foster a sound environment for financial investment.

Due to the information overload on the Internet, it has become extremely critical, especially for the individual investors to know who and how credible the information provider is (see Unsal and Movassaghi, 2001). As observed by Unsal and Movassaghi (2001) some firms may promote certain stocks online to boost their prices without disclosing their relationships to the companies they are pushing. While market efficiency requires that the information is accurate and complete, induced boosting of prices is surely against market efficiency. Investors who lack knowledge about securities trading would be better off with full-service brick and mortar brokers. Investment and research reports on some online broker dealers' web sites can be mistaken by investors as recommendations to buy or sell certain stocks (Higgins, 2002). It has also been questionable if traders get the best possible execution in terms of the best price from their online brokers. Some online brokers also do not provide all the necessary information on risks and returns of different products to investors to enable them to make informed decisions. For example, some of the complaints lodged with the SEC in the US are in connection with broker dealers not disclosing adequate information about when they would sell securities in a margin account, misuse of personal information and allowance of unauthorised access to trading accounts (Higgins, 2002).

Online investors also tend to trade more frequently than do the full-service clients and many tend to trade relying on human emotions. Online trading has thus encouraged short-term and noise trading in the form of what has become known as "online day rapid-fire trading" designed to capture tiny price differentials in stocks, instead of long-term profits from buying and holding securities (Unsal and Movassaghi, 2001). Supporters of short-term traders argue that these traders make a key contribution to the efficiency of financial markets by constantly scouring the markets for arbitrage opportunities, while the critics contend that these traders engage in speculation, leading to excessive and sapping volatility in market prices. Kadapakkam (2000), however, found evidence supporting the argument that removing constraints on short-term trading improves financial markets' pricing efficiency.

Online investing is also known to suffer from the problem of delays and outages. According to Unsal and Movassaghi (2001) and Higgins (2002), there was an outage in America in January and February of 1999. Many of the largest online brokerage firms in America are said to have failed to handle the torrent of trades unleashed by the heady stock market resulting in their systems breaking down (Unsal and Movassaghi, 2001). Online investors could not execute their trades resulting in the loss of financial opportunities.

4.6 The Internet and market efficiency

An efficient market is one with the ability to efficiently process all relevant information. The Internet tends to reduce market frictions in terms of information availability and costs, thus promoting the market towards efficiency. Randomness, in Samuelson's (1965) definition, is achieved through the active participation of many investors seeking greater wealth (Ross, 2002)[4]. These investors tend to pounce on even the smallest informational advantage at their disposal and in so doing, incorporate their information into market prices. In a world of frictionless markets and costless trading, this occurs instantaneously and thus the prices will always fully reflect all the available relevant information.

Over the past couple of years, the Internet, among other events, has spurred investors to reconsider the EMH (West, 2002). This is because the flow of information has become faster with the Internet and surprises are factored in instantaneously (Hill, 2002). The Internet has promoted open-information economies, thereby increasing arbitrage activities and leading to more efficient prices. According to Kamel and

[4] http://www.basicsoftrading.com/journal/2002-4/04-02/

Hussein (2001), today the Internet is a major driving force of change in the global market place. They argued that the world is becoming more and more aware of the opportunities enabled by the Internet as a vital source of information and knowledge at the individual and organisational level. The Internet has also enabled the internationalisation of economies leading to loss of local government control in many cases. New electronic-based services act as middlemen to locate, organise and present information to consumers.

Data and information is, however, valuable if the end-user is able to systematically convert, synthesise and create financial knowledge out of it. According to Yuen, *et al.* (2001), transparency and efficiency are two extremely important issues to users of financial information. With transparency, investors are able to know about the market's operations and its major activities while efficiency refers to the time and effort needed by users to search and retrieve the necessary information. Yuen, *et al.* (2001) remarked that in order to make high quality decisions and narrow the gap between private and institutional investors, both issues need to be solved.

The activities of professional investors focussing on global markets require a medium such as the Internet. These activities range from monitoring the latest price movements, analysing the trends and future performance of certain financial instruments and watching the latest news that may affect the prices. In addition, they need to study the background of the investment environment, complete and comply with some formally required investment procedures, manage portfolios and seek advice from other experts before making a decision (Yuen, *et al.*, 2001). The Internet, as a major information source and communication tool, has made it easier for investors to achieve all this by making information available that covers almost all the major financial markets and instruments in the world. A person with more complete market information is in a much better position to support investment decision-making than is someone whose information is insufficient.

4.6.1 Internet accessibility to the African investor[5]

Emerging markets, in particular, differ from their counterparts in developed nations in their information-related attributes and their institutional infrastructures (Kumar and Tsetsekos, 1999). The free flow of information to all participants is a necessary condition for market efficiency (Kumar and Tsetsekos, 1999) and this may not be the picture in emerging markets where information asymmetry is perceived to be an inherent characteristic. The Internet could be considered an important infrastructure in the efficient operations of stock markets today.

The global Internet market is estimated to have around 150 million users and 44 million hosts in more than 130 countries. However, over 75 percent of computers linked to the Internet are in the USA (Unsal and Movassaghi, 2001) while emerging markets lag much further behind. Of the 816 million people living in Africa in 2001, 1 in every 160 or approximately 5 million people used the Internet (see Table 4.1).

As of mid-2002, the number of dial-up Internet subscribers was close to 1.7 million of which 1.2 million were from South Africa and North Africa and the remainder from the other 49 countries. In Africa, each computer with an Internet or email connection is said to support between 3 - 5 users. This puts the estimates of the total number of African Internet users at around 5 - 8 million with about 1.5 – 2.5 million outside of North and South Africa. While Africa still lags far behind in embracing this new technology it is estimated that an average North American resident has access to around 570 times more international bandwidth than the average African citizen.

Table 4.1: Africa communication and regional Internet statistics*

Africa Communication Statistics 2001			Internet Users by region 2000	
	Proportion of Population	**Population (millions)**	**Region**	**Proportion of Population**
Have a radio	1 in 4	205	Africa	1 in 250-400
Have a TV	1 in 13	62	Latin America & the Caribbean	1 in 30
Have a mobile phone	1 in 35	24	South Asia	1 in 250
Have a fixed line phone	1 in 40	20	East Asia	1 in 43
Have a PC	1 in 130	5.9	Arab States	1 in 166
Use the Internet	1 in 160	5	North America and Europe	1 in 2
Have Pay TV	1 in 400	2	World average	1 in 15

Source: Chipo Mlambo (2003) , University of Stellenbosch Business School
*Information used was obtained from AISI-Connect National ICT Profile on http/www3.sn.apc.org/africa/afstat.htm

[5] Much of the information and statistics in this section was obtained from http/www3.sn.apc.org/africa/afstat.htm

Table 4.2: African country Internet status summary, August 2001

Country	Dialup Internet Subscribers	International Bandwidth (Kbps Outgoing)	Internet Hubs (Number)	Number of ISPs	Population (Millions) 2000	GDP/Capita (USD) 1999	Cities with POPs	Dialup Access Cost (USD)*
South Africa	750000	300000	5	80	44.31	2979	100	40
Algeria	45000	2048	1	4	30.08	1442	4	
Angola	4000	192	1	4	12.09	1684	5	
Benin	4000	1024	1	2	5.78	374	2	
Botswana	25000	14000	1	6	1.57	3252	4	
Burkina Faso	3000	256	1	3	11.31	199	1	42
Burundi	150	64	1	2	6.46	159	1	
Cameroon	2500	256	1	7	14.31	617	2	40
Cape Verde	1800	1024	1	1	0.41	876	1	
Central African Republic	200	64	1	1	3.48	276	1	
Chad	300	64	1	1	7.27	149	1	
Comoros	200	64	1	1	0.66	382	1	
Congo	200	128	1	1	2.79	833	2	
Cote D'ivoire	10000	5120	2	5	16.2	767	2	
D.R Congo	4500	2048	3	5	49.3	400	4	
Djibouti	300	64	1	1	0.62	846	1	
Egypt	80000	112500	3	100	65.98	1195	14	60
Equatorial Guinea	200	64	1	1	0.43	668	1	
Eritrea	1000	128	1	4	3.58	161	5	70
Ethiopia	2500	512	1	1	59.65	103	1	75
Gabon	2500	512	1	2	1.17	5121	2	
Gambia	3000	128	1	1	1.23	284	1	
Ghana	15000	4096	3	8	19.16	372	7	
Guinea	4000	128	3	2	7.71	677	3	
Guinea-Bissau	250	64	1	1	1.13	245	1	
Kenya	35000	6144	1	34	29.01	347	6	123
Lesotho	250	512	2	2	2.06	547	1	
Liberia	75	128	1		2.67	1000	1	
Libyan Arab Jamahiriya	4000	2048	1	1	5.98	6579	1	
Madagascar	8000	2556	2	7	16.36	224	4	
Malawi	2400	1024	3	2	10.75	242	2	
Mali	3000	128	1	5	10.69	230	1	130
Mauritania	550	384	1	5	2.53	455	2	
Mauritius	35000	4096	1	1	1.15	3661	1	
Morocco	80000	136000	1	250	27.87	1218	10	
Mozambique	6000	2048	3	5	18.88	86	4	31
Namibia	15000	3072	2	3	1.66	2051	13	40
Niger	350	192	1	1	10.08	161	1	
Nigeria	50000	9216	5	15	113.5	551	5	40
Reunion	500	576	1	2	0.68	9270	1	
Rwanda	1000	128	3	1	6.6	317	1	
Sao Tome & Principe	200	64	1	1	0.14	358	1	
Senegal	15000	48000	1	8	9	518	1	51
Seychelles	3000	4098	2	2	0.08	6995	1	
Sierra Leone	500	128	1	1	4.57	209	1	
Somalia	250	64	1	1	10.63	169	1	160
Sudan	2000	256	1	1	28.29	364	1	
Swaziland	1200	256	2	2	0.95	1388	2	
Tanzania	20000	4096	3	14	32.1	244	2	
Togo	1700	1536	2	12	4.4	324	1	
Tunisia	70000	41500	1	5	9.34	2144	7	30
Uganda	10000	2048	4	8	20.55	317	1	109
Zambia	6500	3072	3	3	8.78	463	3	
Zimbabwe	20000	5120	1	8	12.68	712	4	46

*Dialup internet access costs calculated for 20 hours a month of local call time plus internet subscription fee
Source: AISI-Connect National ICT Profile on http://www3.sn.apc.org/africa/afrmain.htm

The average cost of using a local dialup Internet account for 20 hours per month in Africa is about US$60/month, including fees and local telephone time. This is extraordinarily high when compared to US$22 in the USA, US$33 in Germany and US$39 across the EU in 2000; yet these countries have per capita incomes at least 10 times greater than the African average. Internet Service Provider (ISP) subscription charges vary greatly from US$10 to US$80 a month. Table 4.2 shows the Internet statistics for African countries.

Though most emerging markets are still way behind in availing information electronically, some such as China (Drew, 1995), India (Siriginidi, 1996) and Egypt (Kamel and Hussein, 2001) have made greater strides in making information available to investors all over the world via the web. According to Kamel and Hussein (2001), Egypt made the Internet a priority for the government and the public sector as a tool for business and socio-economic development since 1994.

The availability of local African content on the Internet is, in particular, still a big challenge. While most African stock exchanges now have websites, the information on some of them is not regularly updated, rendering it useless to investors. In order to develop local content on the Internet, Egypt began implementing the Egyptian Information Highway project in 1995 with the objective of making the Internet more relevant and appealing to Egyptians (Kamel and Hussein, 2001). The greatest strides in making information available electronically have been in the area of investment opportunities, financial markets and services, infrastructural development and research studies. Other projects undertaken by Egypt includes the Capital Exchange Project, which addresses stock trading over the Internet and links the trading community of brokers with potential investors around the world, providing a better mechanism for trading in the Egyptian stock market, and the provision of online financial information related to money and capital markets (Kamel and Hussein, 2001).

4.6.2 The Internet and market efficiency: The African perspective

While stock exchanges around the world have automated to varying degrees and some have eliminated floor trading altogether (Fish and Biekpe, 2002), some African stock markets are yet to adopt electronic trading and settlement. The relatively low trading volumes on African markets result from poor information flows about securities to both institutional and individual investors. Information regarding opportunities that exist on African markets has become more readily accessible online on those markets that have adopted electronic trading and have up-to-date websites. As the market becomes more efficient with electronic trading, investor confidence is heightened, as prices are perceived to reflect the stocks' intrinsic values and thus a reduction in the investors' risk exposure.

Fish and Biekpe (2002) wrote that in May 2002 the Johannesburg Stock Exchange (JSE) converted its Johannesburg Electronic Trading (JET) system to the Stock Exchange Trading Systems (SETS) used on the London Stock Exchange (LSE). Other markets that adopted this trading system include Ghana and Namibia Stock Exchanges. SETS is a world-class, flexible and robust trading platform said to promise improved liquidity and more efficient functionality of the market through providing more in-depth price information, improved efficiency and stronger trade. Transparency and liquidity encourages participation by traders while the new functionality stimulates trade in illiquid stocks, ensures equal access to information, minimises system complexity and facilitates the introduction of new instruments. According to Fish and Biekpe (2002), South African companies cited one of the main reasons for listing offshore to be the privilege to get into a global index, and thereby attracting the tracker funds that follow. SETS allow companies to get these offshore privileges without having to move offshore. The relationship between the JSE and the LSE through their uniform information dissemination component allows the publishing of each other's share price information and thus greater access to information.

The Internet has made online trading, and thus the speedy making of transactions at reduced costs, possible. However, on many African stock markets, except for a few such as South Africa, Tunisia and Egypt, it is still not possible to place orders with stockbrokers online unlike in the United States where the number of on-line investors is said to have increased from 2.2 million in 1998 to about 5.2 million in 2000 (Unsal and Movassaghi, 2001). According to Unsal and Movassaghi (2001), in the US, stockbrokerage firms adopted the Internet technology more extensively than many other sectors in the financial services industry with the number of e-brokerage firms growing from only 12 in 1994 to 120 in 1999. They also noted that according to estimates one in every three equity trades made by retail investors in the US are now placed online and it is expected that over the next 3 to 5 years, nearly all investors will use the Internet to access their accounts.

4.6.3 Empirical analysis

To empirically investigate whether there is a (positive) relationship between stock market development (as measured by size, liquidity and efficiency) and the Internet, a correlation analysis was performed. The assumption made is that the stock exchange is affected more by local residents in the country where it is located, which, though could be true for the restrictive African markets, may not be necessarily true for the open overseas markets. The analysis is done in two parts (a) using data from relatively developed overseas markets including South Africa, the results of which are presented in Table 4.3 and (b) using data from African countries, with results presented in Table 4.4.[6]

Table 4.3: Correlation between Internet users and stock market indicators using cross-sectional time series data

	#Stocks	MC (US$'m)	Value (US$'m)	Turnover	Stock Index	Internet Users	Users % Pop
#Stocks	1						
MC (US$)	0.726**	1					
Value (US$)	0.622**	0.755**	1				
Turnover	0.357**	0.459**	0.711**	1			
Stock Index	-0.170**	0.054	0.057	-0.091	1		
Internet Users	**0.627****	**0.518****	**0.722****	**0.376****	**-0.012**	1	
Users % Pop	**0.215****	**0.149****	**0.413****	**0.347****	**-0.198****	0.590**	1

** Implies significance at the 1% level (2-tailed)
Note: Correlation coefficients of interest in bold
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

The results in Table 4.3 were obtained using Internet statistics[7] for 46 countries for the period between January 1998 and December 2002 and the corresponding stock market data[8]. The Internet statistics were measured over irregular intervals depending

[6] A similar analysis was done using data from the World Development Indicators Fact book 2002, the results of which are presented in Appendix C. In the Appendix more variables are included than is the case in Tables 4.3 and 4.4 and larger sample sizes are used. The results are, however, complementary to those presented in Tables 4.3 and 4.4. Such a task was necessary since the credibility of sources and measurement methods for Internet statistics is still wanting.

[7] The Internet statistics were obtained from the following website: http://www.nua.com/surveys/how_many_online/index.html

[8] The stock market data was obtained from: http://www.world-exchanges.org/index.asp?resolutionX=800&resolutionY=600

on availability (see source). In order to carry out our analysis, the stock market data had to be synchronised with the Internet data. Since the Internet data for each country could not give enough observations to make a meaningful analysis, data for all countries was combined to form a cross-sectional time series.

The results in Table 4.3 show that there is a positive relationship between stock market development indicators (with the exception of stock market indexes) and internet access. These results are highlighted in bold in the matrix table. The lack of relationship between Internet users and the Index cannot be readily explained. It could be a measurement problem due to the different methods of calculation by the different stock exchanges or the dependence of the index on pricing, which has more to do with the valuation of stocks than with the number of investors. The positive relationship between stock market size, as measured by the number of stocks and market capitalisation, and internet access can be explained by the opportunities that the internet avails inspiring more and more companies to get listed. The greater the numbers of people with access to the Internet the greater the continuous valuation of securities. This therefore improves liquidity and the discovery of patterns in stock prices that would be arbitraged away into non-existence, promoting market efficiency.

Table 4.4 uses cross-sectional data from African stock markets. The correlation coefficients of interest are highlighted in bold. All of them are positive though some are not statistically significant. However, the correlation coefficients between the variable, 'Internet users', and the stock market indicators are not only positive, but also highly significant. While the markets used in Table 4.3 are mostly 100 percent open to foreign participation, the African markets used in Table 4.4 are relatively closed or partially open. For developed markets, it is not necessarily domestic investors that impact on the market since they are relatively/wholly open to foreign participation in comparison to their African counterparts. While most African markets are not fully open to foreign participation, local investors also have limited access to the Internet. This, combined with the lack of local African content on the Web, sadly enough, results in African stock markets remaining illiquid and less efficient.

Table 4.4: Correlation between Internet infrastructure and accessibility and stock market indicators using data from Africa

	Users	IntBand	%Users	Fixlines	Mobile	MCap	%MCap	Value	TRatio	Listed
Users	1									
IntBand	0.904**	1								
%Users	0.639*	0.752**	1							
Fixline	0.798**	0.673**	0.196	1						
Mobile	0.534*	0.620*	0.416	0.599*	1					
Mcap	**0.827****	**0.688****	**0.314**	**0.934****	**0.615***	1				
%MCap	**0.739****	**0.725****	**0.749****	**0.451**	**0.694****	0.587*	1			
Value	**0.853****	**0.769****	**0.612***	**0.744****	**0.766****	0.815**	0.857**	1		
TRatio	**0.732****	**0.728****	**0.477**	**0.701****	**0.500**	0.824**	0.560*	0.778**	1	
Listed	**0.728****	**0.509**	**0.090**	**0.868****	**0.432**	0.921**	0.486	0.705**	0.692**	1

** Implies significance at the 1% level (2-tailed)
* Implies significance at the 5% level (2-tailed)
Note: Correlation coefficients of interest in bold

Users=Dialup Internet Subscribers; IntBand=International Bandwidth (Kbps); %Users=Dialup Internet Subscribers as percentage of population; Fixline=Fixed lines 1998 (thousands); Mobile=Mobile Lines 1998 (thousands); MCap=Market Capitalisation Jan 2000 (US$'m); %MCap=Market Capitalisation as percentage of GDP; Value=Value traded; TRatio=Turnover Ratio; Listed=Listed companies
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

4.7 Conclusion

This chapter attempted to highlight the role that the Internet is playing in promoting stock market efficiency. It has been argued that, showing that in the absence of the online media, and assuming the telephone to be the only fastest medium available for information dissemination and transactions ordering, stock markets will not be efficient, especially in the stronger forms. Stock markets around the world are making efforts to improve market efficiency by improving information dissemination, making stock price information accessible to a broader range of investors and introducing electronic or computer-based trading systems.

The Internet has saved technical analysts a lot of trouble and time in that they can now get all the bulky data (historical stock prices and volume traded) they need to study trends dating back several years for any particular stock exchange anywhere across the globe without physically going there to collect it. Data transmitted electronically and online is usually in a ready-to-use format saving the analysts time and effort in uploading it onto their computer systems before they can do their analyses. Easy access to bulky data has also led to the production of software to aid in technical analyses that require large volumes of data such as the learning models, a good example of which is the artificial neural networks.

Investing on the stock market has become more interesting than it was before. Investors now make more informed decisions and not just act on hunches. With stockbrokers availing their research material online, access to these research documents has enabled investors to compare analyses reports from different stockbrokers and research firms. Market participants now have almost equal opportunities to accessing all relevant information. With the Internet, trading has become more discrete as investors can now trade (buy and sell shares) from the comfort of their own homes (online trading) and therefore making it difficult to just follow other investors' actions.

With the positive correlation between most stock market development indicators and Internet access, availing information online and also promoting the infrastructure to improve Internet accessibility can improve stock market liquidity and efficiency. A home telephone and computer are often considered luxury items in some African countries, yet these are the key infrastructures to Internet access. While foreign residents have greater Internet access than African residents, they are restricted in their participation on African stock markets by regulations and lack of online up-to-date local information content from some African stock markets. Unless African governments address these issues, African stock markets will continue to lack in liquidity and efficiency.

5 THE BEHAVIOUR OF STOCK RETURNS ON THE THINLY TRADED AFRICAN STOCK MARKETS

5.1 Introduction

Small stock markets, especially those in Africa, are characterised by infrequent or thin trading. Thin trading causes severe problems and bias in the modelling of stock returns. As a result of thin trading, the horizon over which returns are calculated varies depending on when the share was last traded. On a thinly traded market, the closing price for a particular day may be several days old and the returns will tend to show some dependence not necessarily due to the true return generating process but as a result of the prevalence of zero returns. The majority of these zero-returns are a result of thin trading and are often termed 'false' zero returns in some literature (e.g. Strebel, 1977). The resultant effect will be that zero returns will tend to be followed by zero returns whereas the majority of these zero returns will be a result of the stock not having been traded.

Some researchers, in an effort to dilute the thin trading effect, have resorted to using longer time horizons in the calculation of returns such as monthly and weekly returns to increase the chances of having at least one observation for each time interval. This is because the probability that a stock has been traded in a given time interval increases as the interval is lengthened. The return series also tend to be more normally distributed as the time interval over which returns are calculated in lengthened. Bowie empirically investigated this and concluded thus:

> "An interesting feature of non-normality uncovered is an interval effect in the extent of non-normality of the return distributions. The interval effect manifests itself in that the longer the intervals (e.g. months rather than days) over which the return series is measured, the less divergent the distribution is from the normal distribution. " (Bowie, 1994: 4-2)

However, in using these longer time horizons there is a component of thin trading that most researchers tend to ignore. This is known as, 'the price age', which Bowie (1994) referred to as the month-end and week-end price ages when monthly and weekly returns are considered respectively[1]. The price age is defined as the time that lapses between the last trade in a given period and the end of that period. This price age factor is important in that when a share is not traded at the end of a given time interval, then the price at which the share was last traded is incorrectly taken to be the price at the end of the interval under perspective.

Another class of researchers on emerging markets have tried to control for the thin trading bias by excluding zero returns (e.g. Kiweu, 1991). This action is a result of an incorrect assumption that all zero returns are a result of thin trading which is not necessarily true. Some zero returns are part of the true return generating process and the beauty of the trade-to-trade approach is partly reflected in that true zero returns are retained in the data set.

5.2 Literature review

Though thin trading is less severe on the developed markets than on emerging markets, studies on the effect of thin trading on a number of stock market attributes are concentrated more on the former than on the latter. Thin trading is often termed the Fisher effect in honour of the first person to recognise its importance in modelling stock prices (e.g. in Bowie, 1994; Campbell, *et al.,* 1997). Research worth noting in the development of models of nontrading include Atchison, *et al.* (1987); Cohen, *et al.* (1980, 1983); Cohen, *et al.* (1978); Dimson (1979); Lo and MacKinlay (1988, 1990a) and Scholes and Williams (1977) (see Campbell, *et al.* (1997)).

On African stock markets, with the exception of the JSE, no known research has been done to investigate the effect of thin trading on any of the stock market attributes such as market efficiency. In tests for market efficiency, some of the results have been

[1] Even in daily returns, there is a price-age component that is currently ignored since the shortest time, especially in emerging markets, that the price is recorded is a day, rather than an hour or every 30 or 15 minutes as might be case in developed markets.

contradictory. For example, while Chiwira (2001) concluded that the Zimbabwe Stock Exchange is a weak-form efficient market, Magnusson and Wydick (2002) and Smith and Jefferis (2002) concluded otherwise.

Other researchers could not make decisive conclusions due to other uncontrolled factors, such as thin trading. Bundoo (2000), for example, suggested that his results of a strong positive autocorrelation in returns on the Port Louis Stock Exchange of Mauritius should be treated with caution since this could be evidence of time-varying risk premiums or the infrequent trading of shares. Asal (2000) adjusted returns using a method due to Miller, *et al.* (1994). According to him, infrequent trading tends to induce false autocorrelation in the return series. Strebel (1977, 1978) considered the efficiency of the JSE "a half truth" because of thin trading in about half of the shares listed on the JSE. Dezelan (1999) found some evidence of autocorrelation in the index returns of the Ljubljana Stock Exchange of Slovenia and suggested that infrequent trading in some shares could have induced this. Osei (2002) highlighted the thinness of trading activities on the GSE as one of the shortcomings to be considered in assessing his results that the GSE is not efficient. Bekaert and Harvey (2002) pointed out that emerging market equity returns have higher order serial correlation than developed markets, which they described as being symptomatic of infrequent trading and thus the slow adjustment to current information.

This prevailing market microstructure, known as thin trading, makes some of the efficiency testing models not directly applicable to African markets. The differences in the business and economic environments between emerging and developed markets necessitate adjustments of certain models before they are applied to the former. Most, if not all, models and testing methods have been developed with specific characteristics of markets in mind. These include high levels of liquidity, actively traded shares, few institutional impediments and rationally-behaved investors. In the context of African markets, some of these characteristics are not satisfied. Concerning trading activities, some stocks may not be traded for more than 75 percent of the time (see Table 5.1).

Table 5.1: Summary statistics for stock exchanges covered

Stock Exchange	No. of trading days	No. of stocks investigated*	Number of stocks in each category of thin trading			
			$0 < p \leq 0.25$	$0.25 < p \leq 0.50$	$0.50 < p \leq 0.75$	$0.75 < p \leq 1.00$
Egypt	1342	54	29	9	16	9
Kenya	1366	30	11	8	11	10
Morocco	1349	27	13	5	9	8
Zimbabwe	1353	31	4	17	10	8

* Please note that the most thinly traded stocks are excluded from the investigations, that is, those with thin trading frequencies above 75 percent.
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

5.3 Data

The data used in this analysis are continuously compounded returns. These are calculated using daily closing stock prices, dividends and volume traded for the period from 2 January 1997 to 31 May 2002 for four African stock markets, namely Egypt, Kenya, Morocco and Zimbabwe. This data was obtained from DataStream and comparisons were made with samples from other primary sources (i.e. the Nairobi Stock Exchange for Kenya, Casablanca Stock Exchange for Morocco, BARDNET and Kingdom Stockbrokers for Zimbabwe) to determine reliability. The volume traded data was used to determine the trading frequency and duration of nontrading of the different stocks.

The stock returns used are for individual companies listed rather than the market index, a vital approach, especially in the African markets context. Although some studies use index returns, these are aggregate and tend to average out any correlation that might exist in the individual returns. The market index can give a false impression that the stocks on the respective market are well traded, when in actual fact trade is concentrated in a few big blue chip stocks with a heavy weighting in the market index. An example is the Ashanti Goldfields Corporation in Ghana taking up about 75 percent of total market capitalisation on the GSE. The majority of stocks on African markets are very small and it is generally agreed that the most thinly traded stocks are small firms. Whereas most blue chip stocks on African stock markets are foreign firms or multinationals, the small stocks are mostly local companies and are mainly affected by the local political, economic, industrial and company specific environments.

5.3.1 Data series

The data series used in efficiency testing are either simple net returns (also referred to as rate of returns) or continuously compounded returns (i.e. log returns or change in log prices). The two series are calculated as follows:

Simple net return: $$r_t = \frac{P_t + D_t}{P_{t-1}} - 1 \tag{5.1}$$

Continuously compounded return:

$$R_t = \ln(1 + r_t) = \ln\left(\frac{P_t + D_t}{P_{t-1}}\right) = \ln(P_t + D_t) - \ln(P_{t-1}) \tag{5.2}$$

where r_t is the simple return on the asset in period t, P_t and P_{t-1} are the prices of the asset in period t and $t-1$ respectively, D_t is the dividend paid on the asset, which went ex-dividend in period t, R_t is the natural logarithm of simple gross returns or continuously compounded returns in period t, and " ln " is the natural logarithm operator.

The most commonly used return series in empirical research or in tests for the random walk is the continuously compounded return. According to Fama (1965), changes in log prices rather than simple price changes are used for the following three reasons:

1. The change in log prices is the yield, with continuous compounding from holding the security for that day
2. Logarithms tend to neutralise the increasing nature of the variability of simple price changes
3. For changes less than 15 percent, the log price change is very close to the percentage price change.

Campbell, *et al.* (1997) also gave justification for the use of logarithmic returns, which mainly pertains to the frequency or probability distributions of returns. Distributions can either be conditional or unconditional and one version of the RWH assumes that the two are equal. Although in the event that the two differs, it is usually the conditional distribution that takes presidency in testing for predictability, the unconditional distribution is not without interest especially where predictability is expected to be minimal.

According to Campbell, *et al.* (1997), the IID-normality assumption of some models of return behaviour suffers from two important drawbacks, and these are:

1. Most financial assets exhibit limited liability such that the largest loss an investor can realise is his total investment and nothing more, which is violated by the normality assumption. In order to avoid this limited liability problem, the normality assumption is rather used on log returns.
2. If single period returns are assumed to be normal (for simple returns), the multi-period returns cannot also be normal since they are products of the single period returns. Since continuously compounded multi-period returns are a sum, rather than a product, of single-period continuously compounded returns, both the single-period and multi-period returns will share the same distribution. Therefore one can assume that log returns are normally distributed and the same distribution will hold for returns of all time intervals.

5.3.2 Trade-to-trade returns

Due to thin trading the returns in this thesis are calculated on a trade-to-trade basis in an effort to counter the thin trading effect. Continuously compounded returns, usually calculated using equation (5.2), are calculated using prices only for those days when trade actually took place. Therefore the intervals over which returns are calculated are not regularly spaced as required in basic time series analysis. The length of each interval (denoted by k_t) in this case depends on the number of days the stock was not traded. With this observation in mind, the trade-to-trade counterparts of equation (5.1) and equation (5.2) are more appropriately written as:

Simple net return: $$r_t(k_t) = \frac{P_t + D_t}{P_{t-k_t}} - 1 \qquad (5.3)$$

Continuously compounded return:

$$R_t(k_t) = \ln(1 + r_t(k_t)) = \ln\left(\frac{P_t + D_t}{P_{t-k_t}}\right) = \ln(P_t + D_t) - \ln(P_{t-k_t}) \qquad (5.4)$$

where $R_t(k_t)$ is the realisable return in period *t*, given that there was trade in period *t*; P_t is the stock's closing price in period *t*; D_t is the dividend per share on a stock going ex-dividend in period *t*; P_{t-k_t} is the price of a stock on the previous consecutive traded day taking place k_t periods in the past; and k_t is the length of time between the trade in period *t* and the previous successive trade.

k_t is variable over time as indicated by the time-subscript *t*. It is given by the following formula as in Bowie (1994)[2]:

$$k_t = 1 + \tau_t + I_{t-\tau_t-1} - I_t \qquad (5.5)$$

where k_t is as defined above; τ_t is the number of non-traded days between successively traded days; and I_t is the price age at the end of day *t* assuming there was trade on day *t*, with mean μ_I and variance σ_I^2.

5.4 Modelling methodology

The continuously compounded returns, henceforth returns in this thesis, are calculated using the trade-to-trade approach, that is, by using prices only for those days when trade actually took place. This is done using equation (5.4) in section 5.3.2 above.

[2] Note the change of notation from that used in Bowie (1994). The variables k_t and τ_t are given as D_t and k_t respectively in Bowie (1994). The change in notation is to avoid confusion with the other variables used in this thesis.

However, since the highest frequency with which closing stock prices are recorded on African stock markets is daily, that is, at the end of each trading day rather than, for example, hourly, the price age when daily returns are used is indeterminate. Even if this was not the case and closing prices for periods shorter than a day were available, such as hourly or every half an hour, the chances of a stock having traded in that interval are very slim, especially in the context of African markets where thin trading is a serious problem.

If another variable is introduced to represent the duration of nontrading or the length of time a stock did not trade, which can be denoted by γ_t, the duration of nontrading in equation (5.5) above will be given by:

$$\gamma_t = \tau_t + I_{t-\tau_t-1} - I_t \tag{5.6}$$

Equation (5.5) will thus become:

$$k_t = 1 + \gamma_t \tag{5.7}$$

As mentioned earlier, the day-end price age is not yet of interest in the African markets context since thin trading is still a serious problem even when measured in days, weeks or even months. Again it is not possible to get historical closing prices recorded for periods shorter than a day for African stock markets. Ignoring this price age component, therefore gives us $\gamma_t = \tau_t$, which means the duration of nontrading is just equal to the number of days not traded.

In time series, it is required that observations be taken at equally spaced time intervals. Considering the return series given by Equation (5.4), there is variability in the interval lengths over which returns are measured. According to Bowie (1994), this variability in the interval length is an integral part of the trade-to-trade estimator. It is determined by the variability in k_t from period to period as reflected by the time subscript *t*. Each return in period *t* is a k_t-period return rather than a standard one-period or multi-period return. These returns over varied interval lengths may not have the same frequency distribution, which may vary depending on the length of the interval. For example, the extent of non-normality in the variances and means of the return series tend to depend on the length of the interval over which returns are measured. Bowie (1994) pointed out that "because of the interval effect in non-normality, the distribution of returns over various lengths will need to change depending on the length of the interval". He went on to say that:

> "The existence of the interval effect ....can be observed in that the extent of non-normality in the return series depends on the length of the interval over which returns are measured" (Bowie, 1994: 4-4)

Normality depends on four moments, the mean, the variance, the skewness and the kurtosis and these tend to depend on the length of the interval over which the observations (in this case returns) are measured. For example the variances of 5-day or weekly returns are expected to be approximately 5 times the variances of daily returns (see Bowie, 1994; Fama, 1965). The variance ratio test of Lo and MacKinlay (1988), now common in testing the randomness of stock returns, is probably based on this assumption. According to Bowie:

> ".....it would appear reasonable that the average weekly return should be approximately five times the average daily return, and that the variance should be similarly increased five-fold in going from daily to weekly returns" (Bowie, 1994: 4-8).

In a simulation study, Bowie (1994) found the variances and means of the return series to increase in proportion to the length of the interval over which they are measured while the kurtosis showed a tendency to decrease as the interval length increases. No intuitive model was apparent for the coefficient of kurtosis while for the means and variances of returns, the following models, respectively, were observed:

$$\bar{r}_p = p \times \bar{r} \qquad (5.8)$$

$$\bar{\sigma}_p^2 = p \times \bar{\sigma}^2 \tag{5.9}$$

where $\bar{r}_p$ and $\bar{\sigma}_p^2$ are the average mean and variance of returns over an interval of length p, and $\bar{r}$ and $\bar{\sigma}^2$ are constants interpretable as the average mean and variance of daily returns respectively. These models are vital in the arguments that follow.

For continuously compounded returns, multi-period returns are a sum of one-period returns. Therefore each return given by Equation (5.4) is a sum of what Campbell, *et al.* (1997) called 'virtual returns' as follows:

$$R_t(k_t) = R_t + R_{t-1} + R_{t-2} + \ldots + R_{t-k_t+1} = \sum_{k=0}^{k_t-1} R_{t-k} \tag{5.10}$$

where k are the previous consecutive periods of no trade; R_t is the return over equally-spaced time intervals (virtual return), which is daily in this case; and $R_t(k_t)$ and k_t are as described before.

In order to reduce the problem caused by irregular intervals, the trade-to-trade (TOT) returns can be standardised by weighting each TOT return by the number of days between trades (k_t). Of note is that this adjustment is only applicable to continuously compounded returns since it comes from the fact that each k_t-period return is a sum of single period returns.

From equation (5.4), the single period return (denoted by $\tilde{R}_t$) can, therefore, be approximated by weighting the observed trade-to-trade return, $R_t(k_t)$, by k_t, the number of days between trades, as follows:

$$\tilde{R}_t = \frac{1}{k_t} R_t(k_t) = \frac{1}{k_t}\left[\ln(P_t + D_t) - \ln(P_{t-k_t})\right] \tag{5.11}$$

where $\tilde{R}_t$ is the approximate one-day return after adjusting for the interval effect.

Another rationale for this kind of adjustment is very simple. For a thinly traded stock, there are delays in price adjustments (lagged response), especially in response to information that affects the aggregate market. A thinly traded stock tends to make a once-off adjustment for information arriving in the market on a given day, plus that which arrived during the consecutive period of nontrading. If this is the case, then the absolute magnitude of returns preceded by a period of nontrading are expected to be higher than those preceded by another trading period, given that the form of the information being adjusted for is the same. In other words, a positive relationship is expected between the magnitude of TOT returns given by Equation (5.4) and the number of days between trades. The hypothesis is proved by finding the correlation between the absolute TOT returns and the number of days between trades. The results will be discussed under the empirical evidence. According to Bowie (1994), it is plausible that returns increase proportionally to the length of the interval over which they are measured.

5.4.1 Alternative adjustment

As outlined in an earlier section, the variance of returns increases in proportion to the interval length. In TOT returns where there is variability in the interval lengths, the variance is also expected to be variable and the assumption of homoscedasticity (constant variance) is violated. On the contrary, there will be heteroscedasticity in the modelling of returns induced by thin trading. Though heteroscedasticity is generally known to be less serious in time series data than in cross sectional data, its presence in this case results from the presence of outliers most of them arising from the thin trading effect. Under normal circumstances, variables in time series data tend to have similar orders of magnitude because they are generally collected for the same entity over a period of time, while their observations are assumed to be for equally-spaced intervals.

From the literature and also from Bowie's findings, the variances of 5-day or weekly returns are expected to be 5 times the variances of daily returns. For k_t-period returns, the variance is thus expected to be k_t times the variance of daily returns.

Considering the random walk model without drift, given in natural log of prices observed only when the stock was traded, written as follows:

$$p_t = p_{t-k_t} + \varepsilon_t \tag{5.12}$$

where $p_t = \ln(P_t + D_t)$ and $p_{t-k_t} = \ln(P_{t-k_t})$, from the discussions above, the nature of heteroscedasticity is expected to be of the form:

$$E(\varepsilon_t^{\,2}) = k_t \sigma^2 \tag{5.13}$$

If instead of adjusting TOT returns as in equation (5.11) to get the approximate daily returns, one can decide to model the TOT returns as given by equation (5.4) and adjust for heteroscedasticity. This can be done by dividing all the terms in the random walk model by $\sqrt{k_t}$ as follows (see Gujarati, 1995):

$$\frac{p_t}{\sqrt{k_t}} = \frac{p_{t-k_t}}{\sqrt{k_t}} + \frac{\varepsilon_t}{\sqrt{k_t}} \tag{5.14}$$

Equation (5.14) is equivalent to:

$$\breve{R}_t = \breve{\varepsilon}_t \tag{5.15}$$

where $\breve{R}_t = \dfrac{R_t(k_t)}{\sqrt{k_t}}$ is the heteroscedasticity-adjusted return

and $\breve{\varepsilon}_t = \dfrac{\varepsilon_t}{\sqrt{k_t}}$ is heteroscedasticity-adjusted noise or abnormal return

Heteroscedasticity has got serious consequences if one is to use ordinary least squares estimation. The estimation done using the adjustment given above is known as the weighted least squares (WLS). If heteroscedasticity is not adjusted for, the usual hypothesis testing procedures would become dubious since estimators will no longer have the minimum variance quality.

The difference between the two adjustments is that with equation (5.11), TOT returns are divided by k_t, while with equation (5.14) or equation (5.15), the division is by $\sqrt{k_t}$. However, the first adjustment, used to approximate one-day returns for each interval is also likely to reduce the heteroscedasticity supposedly induced by thin trading. Therefore for the next sections the adjusted TOT returns would refer to TOT returns adjusted using equation (5.11).

5.4.2 Tests

If log stock prices follow a random walk without drift, which approximates a martingale, the continuously compounded returns would be a white noise process of the form[3]:

$$\tilde{R}_t = \varepsilon_t \tag{5.16}$$

This chapter follows the traditional methodologies of testing for independence in stock returns, that is, the serial correlation coefficients test (parametric) and the runs test (nonparametric). For the return $\tilde{R}_t$, the serial correlation coefficient for lag s is given by:

$$\rho_s = \frac{\text{cov}(\tilde{R}_t, \tilde{R}_{t-s})}{\text{var}(\tilde{R}_t)} = \frac{\sum_{t=1}^{n-s}\left(\tilde{R}_t - \overline{\tilde{R}}\right)\left(\tilde{R}_{t-s} - \overline{\tilde{R}}\right)}{\sum_{t=1}^{n-s}\left(\tilde{R}_t - \overline{\tilde{R}}\right)^2} \tag{5.17}$$

[3] For a random walk with drift or a sub-martingale, the return process will be given by: $\tilde{R}_t = \mu_t + \varepsilon_t$

If the serial correlation coefficients are significantly different from zero, the hypothesis of a random walk can, therefore, be rejected. On the other hand, conclusions from the runs test are made by comparing the observed number of runs with the expected number of runs. If the two are significantly different from each other, then the random walk hypothesis is rejected.

The serial correlation test, like any other parametric test, depends on the distribution of the data series. In most cases the normal distribution is assumed in order to simplify things. It is important to investigate to what extent this normality assumption holds or to what extent it approximates the distribution of the underlying series. If there is significant deviation from normality, then the more reliable test in this regard will be the runs tests (or any other parametric test, some of which were stated in section 3.2.3).

5.5 Empirical evidence

A number of hypotheses have been uncovered in the preceding sections. It is worthwhile to summarise them here before presenting the results.

1. H_0: There is a positive correlation between absolute TOT returns and the number of days between trades

   H_1: There is no positive relationship between absolute TOT returns and the number of days between trades
2. H_0: Stock returns are normally distributed

   H_1: Stock returns are not normally distributed
3. H_0: Stock price changes or returns follow a random walk

   H_1: Stock price changes do not follow a random walk

5.5.1 Correlations between returns magnitude and the interval lengths

In investigating whether there is a positive relationship between the absolute TOT returns and the number of days between trades, the Spearman's rank correlation test is used. The reason for using this test is that, unlike the Pearson's correlation test, it is nonparametric and thus does not depend on the normality assumption. Using the

Kolmogorov-Smirnov normality test, normality is rejected in the two variables, the 'absolute returns' and the 'interval lengths'.

The Spearman's rank correlation coefficients are highly significant and positive indicating a positive relationship and in support of the hypothesis that there is a positive correlation between absolute TOT returns and the number of days between trades (see Table 5.2).

Table 5.2: Number of stocks with significant correlation coefficients between the absolute TOT returns and the number of days between trades for the specified levels of significance using the Spearman's rank correlation test

Stock Exchange	Significant				Insignificant		Correlation tendency
	1% level of significance		5% level of significance		5% level of significance		
	Positive	Negative	Positive	Negative	Positive	Negative	
Egypt	25	-	9	-	17	3	Positive
Kenya	13	-	7	-	8	2	Positive
Morocco	12	-	4	-	10	1	Positive
Zimbabwe	31	-	-	-	-	-	Positive

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

For Egypt, the Spearman correlation coefficients are significant and positive at the 1% level in 25 stocks and at the 5% level in 9 stocks. Though the correlation coefficients are not significant for the remaining stocks, they are all positive, except for EGCM, PFIZ and SGEN with negative coefficients of -0.007, -0.001 and -0.022, respectively, which are all not significantly different from zero (see Table 5.3, column 5). The insignificance in the correlation coefficients of these other stocks can be explained by the pattern with which information comes into the market. If positive (negative) news, not immediately unadjusted for, is followed by negative (positive) news, then when the stock finally trades and adjust for this lagged information, the magnitude of the returns will tend to cancel out, therefore giving returns of a smaller magnitude. Therefore the hypothesis tested is based on the assumption that the returns accumulated during nontrading are of the same sign such that on the day of trading, given the duration of nontrading, the return will be either a larger negative return or a larger positive return in magnitude.

Table 5.3: Egypt – Thin trading, correlations between TOT returns in absolute terms and the number of days between trades, normality tests and the runs test for TOT-adjusted returns

Stock		Thin trading (a)		(b)[r]	Normality Tests (c)					Runs Test (d)	
	No. of Observations	Ave.# days between trades	Proportion of non-traded days	Spearman's Rank Correlations	Skewness	Std. Err.	Kurtosis	Std. Err.	Kolmogorov -Smirnov Z	No. of Runs	Z-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)[s]	(10)	(11)
ALXP	397	3.36	0.703	0.157**	-0.201	0.122	0.941	0.244	2.483**	208	2.008*
ALXW	804	1.66	0.399	0.025	-0.480	0.086	3.269	0.172	2.390**	329	-5.102**
AISC	573	2.28	0.572	0.210**	-0.230	0.102	0.807	0.204	3.016**	280	-0.077
APCC	1192	1.12	0.111	0.027	2.479	0.071	32.304	0.142	3.138**	575	-1.251
ABCE	536	2.48	0.599	0.134**	0.168	0.106	0.801	0.211	2.496**	212	-4.594**
CAPL	538	2.47	0.598	0.047	-0.346	0.105	1.504	0.210	2.972**	235	-1.964*
CIB	1275	1.05	0.049	0.076**	-0.578	0.069	23.649	0.137	2.933**	546	-5.179**
DLNS	573	2.34	0.572	0.058	-0.035	0.102	1.190	0.204	3.399**	267	-0.565
EAB	1250	1.07	0.068	0.097**	-0.150	0.069	1.649	0.138	2.589**	553	-3.968**
EDLT	1273	1.05	0.051	0.136**	-0.098	0.069	11.547	0.137	3.957**	595	-2.146*
EDBK	1208	1.08	0.098	0.079**	-1.344	0.070	21.843	0.141	3.892**	610	0.393
EFND	1231	1.09	0.082	0.111**	0.050	0.070	1.676	0.139	2.933**	612	-0.244
EGCM	631	2.12	0.529	-0.007	-0.257	0.097	9.164	0.194	2.439**	286	-2.011*
EGSR	925	1.45	0.310	0.138**	0.220	0.080	1.334	0.161	2.490**	452	-0.747
ECAB	1270	1.05	0.052	0.067*	-3.846	0.069	68.774	0.137	3.311**	617	-0.9
ELKA	1253	1.07	0.064	0.062*	-1.553	0.069	18.648	0.138	2.177**	568	-3.332**
ELND	655	2.02	0.511	0.253**	-0.025	0.095	0.084	0.191	1.784**	306	-1.759
ELSG	387	3.39	0.711	0.230**	0.168	0.124	1.534	0.247	2.631**	172	-1.932
EWBK	1264	1.06	0.057	0.095**	-0.566	0.069	6.280	0.138	3.097**	622	-0.612
ETBC	1240	1.08	0.075	0.083**	0.301	0.069	2.473	0.139	3.142**	572	-2.776**
EXOL	722	1.85	0.461	0.125**	0.198	0.091	0.338	0.182	2.532**	336	-1.806
HHSE	809	1.65	0.396	0.031	0.381	0.086	2.497	0.172	2.903**	375	-2.139*
HCST	494	2.71	0.631	0.038	0.071	0.110	-0.638	0.219	2.020**	184	-5.704**
HPCC	1168	1.15	0.129	0.147**	0.423	0.072	3.673	0.143	3.861**	513	-3.957**
INEG	770	1.74	0.425	0.074*	0.033	0.088	-0.212	0.176	1.890**	379	-0.463
KZAY	989	1.35	0.262	0.008	2.229	0.078	35.306	0.155	2.515**	454	-2.591**
MPHS	636	2.10	0.525	0.138**	0.014	0.097	2.320	0.194	2.806**	334	1.594
MIBK	1256	1.07	0.063	0.046	-1.124	0.069	14.038	0.138	3.071**	582	-2.568**
MDGM	1252	1.07	0.066	0.050	-0.057	0.069	6.185	0.138	3.139**	630	0.231
MWST	1262	1.06	0.059	0.074**	-0.598	0.069	17.829	0.138	3.365**	604	-1.257
MSCM	1260	1.06	0.060	0.105**	0.084	0.069	-0.830	0.138	2.175**	582	-2.71**
MHOT	1092	1.23	0.186	0.060*	0.096	0.074	-0.309	0.148	1.750**	545	-0.089
MOIL	537	2.43	0.599	0.105*	-0.182	0.105	2.212	0.210	3.523**	264	0.783
MHBK	839	1.60	0.374	0.234**	-0.182	0.084	-0.787	0.169	1.819**	415	-0.282
MHIN	634	2.11	0.527	0.033	0.297	0.097	1.693	0.194	2.994**	287	-1.953
NTCM	1064	1.26	0.206	0.068*	0.188	0.075	0.543	0.150	2.104**	484	-2.972**
NBDV	1158	1.16	0.136	0.099**	-0.077	0.072	-0.436	0.144	1.413*	585	0.339
NCAI	1213	1.10	0.095	0.045	-0.620	0.070	17.484	0.140	3.674**	553	-3.075**
NLMT	1180	1.13	0.120	0.028	0.232	0.071	0.699	0.142	2.224**	578	-0.735
NLPM	663	2.02	0.505	0.208**	-0.383	0.095	5.561	0.190	2.620**	296	-2.293*
NCTY	1253	1.07	0.065	0.045	0.142	0.069	0.786	0.138	2.775**	571	-2.939**
NSGB	1188	1.12	0.114	0.051	-1.115	0.071	12.274	0.142	3.310**	600	0.433
ORNT	345	3.87	0.742	0.097	3.274	0.131	33.109	0.262	2.044**	137	-3.87**
PCHC	1244	1.08	0.072	0.101**	0.660	0.069	7.575	0.139	3.011**	593	-1.685
PFIZ	1137	1.18	0.152	-0.001	-0.025	0.073	-0.588	0.145	1.987**	524	-2.571**
RKTA	749	1.79	0.441	0.023	0.038	0.089	-0.840	0.178	2.551**	315	-4.326**
SCAI	1229	1.09	0.083	0.076**	0.107	0.070	3.345	0.139	2.714**	616	0.115
SGEN	382	3.51	0.715	-0.022	0.012	0.125	0.383	0.249	3.117**	171	-1.711
SZCN	937	1.43	0.301	0.104**	0.154	0.080	21.061	0.160	3.213**	475	0.475
SZCM	1277	1.05	0.048	0.060*	-0.059	0.068	1.654	0.137	2.689**	598	-2.322*
TORA	1267	1.06	0.055	0.064*	0.140	0.069	2.981	0.137	3.714**	564	-3.933**
UHDV	1103	1.21	0.177	0.018	0.348	0.074	5.019	0.147	1.735**	517	-2.03*
UPAC	546	2.44	0.592	0.090*	0.131	0.105	-0.626	0.209	1.820**	234	-3.414**
UPGL	1261	1.06	0.060	0.112**	0.117	0.069	11.326	0.138	3.449**	580	-2.792**

* Implies significance at the 5% level (2-tailed). ** Implies significance at the 1% level (2-tailed).

[r] Correlations between unadjusted TOT returns and the number of days between trades (i.e. one plus the duration of nontrading)

[s] All the Kolmogorov-Smirnov Z-statistics were significant at less than the 1% level (2-tailed) except NBDV, which was significant at the 5% level

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

In Kenya, 13 stocks have significant correlation coefficients at the 1% level while 7 have coefficients significant only at the 5% level. In both cases the significance is for positive correlation in all the stocks. Of the 10 stocks with insignificant coefficients, 8 of them are positive. The two negative coefficients are, like in the Egyptian case, very small, almost zero, that is, -0.008 and -0.002, and these are for the two banking institutions, BBK and NBK respectively (see Table 5.4, column 5).

Table 5.4: Kenya – Thin trading, correlations between TOT returns in absolute terms and the number of days between trades, normality tests and the runs test for TOT-adjusted returns

		Thin trading (a)		(b)[r]	Normality Tests (c)					Runs Test (d)	
Stock	No. of Observations	Ave.# days between trades	Proportion of non-traded days	Spearman's Rank Correlations	Skewness	Std. Err.	Kurtosis	Std. Err.	Kolmogorov -Smirnov Z	No. of Runs	Z-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)[s]	(10)	(11)
BAM	763	1.79	0.441	0.17	-0.307	0.089	10.261	0.177	4.882**	361	1.441
BAT	1012	1.35	0.258	0.120**	0.690	0.077	68.391	0.154	5.900**	467	1.571
BBK	1338	1.02	0.020	-0.008	-0.114	0.067	30.224	0.134	7.040**	595	2.054*
BBD	617	2.21	0.548	0.145**	0.875	0.098	58.439	0.196	5.642**	241	-0.812
CRB	371	3.66	0.728	0.188**	0.318	0.127	8.987	0.253	3.557**	167	0.264
CBG	595	2.29	0.564	0.056	0.620	0.100	27.985	0.200	4.647**	290	1.176
CFC	582	2.34	0.573	0.066	0.179	0.101	15.941	0.202	4.933**	256	-0.638
CMC	456	2.98	0.665	0.063	-0.262	0.114	13.402	0.228	3.982**	199	-0.56
DTK	733	1.85	0.463	0.129**	-2.757	0.090	36.349	0.180	5.231**	340	1.357
EBL	1207	1.13	0.116	0.069*	-0.068	0.070	10.570	0.141	6.058**	571	3.289**
ECB	377	3.62	0.723	0.224**	1.378	0.126	15.416	0.251	4.117**	177	-0.268
FST	963	1.41	0.294	0.024	0.023	0.079	7.466	0.157	4.543**	503	3.722**
GWK	398	3.41	0.708	0.207**	3.431	0.122	36.046	0.244	4.243**	155	-1.796
HFC	1230	1.11	0.099	0.068*	-0.624	0.070	25.628	0.139	5.233**	630	3.656**
ECD	1126	1.21	0.175	0.054	-0.035	0.073	13.096	0.146	5.498**	540	2.849**
JUB	717	1.90	0.474	0.128**	-0.094	0.091	5.979	0.182	4.500**	356	2.254*
KCB	1327	1.03	0.028	0.061*	-1.330	0.067	17.688	0.134	6.140**	606	0.09
KNL	348	3.89	0.745	0.216**	2.878	0.131	15.717	0.261	4.163**	163	0.566
KNM	716	1.88	0.475	0.119**	-2.797	0.091	50.530	0.182	5.185**	308	-1.698
KPL	1149	1.19	0.158	0.087**	1.683	0.072	27.969	0.144	5.113**	536	0.378
NBK	1244	1.10	0.089	-0.002	-0.758	0.069	15.280	0.139	5.178**	648	3.782**
NIC	1240	1.10	0.092	0.058*	-0.252	0.069	31.070	0.139	5.143**	611	2.47*
NMG	1177	1.16	0.138	0.103**	-0.576	0.071	42.790	0.142	6.592**	567	4.194**
RVP	909	1.50	0.335	0.085*	-0.505	0.081	10.223	0.162	4.840**	488	5.26**
SSIN	576	2.36	0.577	0.133**	-2.630	0.102	26.860	0.203	4.747**	264	0.722
SBK	1326	1.03	0.029	0.004	-8.232	0.067	178.435	0.134	6.475**	601	1.558
SNG	467	2.91	0.657	0.98*	0.399	0.113	4.855	0.225	3.855**	230	0.383
TTL	877	1.56	0.357	0.062	-0.451	0.083	12.090	0.165	5.074**	414	0.133
UCH	1221	1.12	0.105	0.097**	0.109	0.070	59.734	0.140	5.738**	620	4.82**
UNG	662	2.04	0.515	0.098*	-11.910	0.095	242.193	0.190	6.495**	291	-1.637

* Implies significance at the 5% level (2-tailed).
** Implies significance at the 1% level (2-tailed).
[r] Correlations between unadjusted TOT returns and the number of days between trades (i.e. one plus the duration of nontrading)
[s] All the Kolmogorov-Smirnov Z statistics were significant at less than the 1% level (2-tailed)
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

The lack of correlation in these two stocks is probably a result of lack of strong variability in the interval lengths. These two stocks are less thinly traded, with both BBK and NBK having thin trading frequencies of only 2 percent and 8.9 percent and average interval lengths of only 1.02 days and 1.10 days respectively[4]. One other bank

[4] Or a duration of nontrading of 0.02 days and 0.10 days respectively, where the duration of nontrading is equal to the number of days between trades less one.

in the sample, SBK, compares well with BBK and NBK. With a thin trading frequency of only 2.9 percent, although the correlation coefficient for this stock is positive, that is, 0.004, it is again not significantly different from zero. Therefore the relationship hypothesised becomes more evident and stronger as we move from actively traded to thinly traded stocks.

Table 5.5: Morocco – Thin trading, correlations between TOT returns in absolute terms and the number of days between trades, normality tests and the runs test for TOT-adjusted returns

Stock		Thin trading (a)		(b)[r]	Normality Tests (c)					Runs Test (d)	
	No. of Observations	Ave.# days between trades	Proportion of non-traded days	Spearman's Rank Correlations	Skewness	Std. Err.	Kurtosis	Std. Err.	Kolmogorov -Smirnov Z	No. of Runs	Z-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)[s]	(10)	(11)
ATH	352	3.81	0.738	0.039	2.388	0.130	29.264	0.259	4.594**	170	0.638
BCE	1336	1.01	0.009	0.039	0.107	0.067	18.519	0.134	5.832**	597	-2.257*
BCI	1122	1.20	0.168	0.039	0.201	0.073	3.980	0.146	5.594**	495	0.294
BCM	1258	1.07	0.067	0.025	0.749	0.069	12.363	0.138	7.508**	491	-3.402**
BDE	1088	1.24	0.193	0.103**	-1.294	0.074	19.095	0.148	5.807**	511	1.242
BNM	373	3.58	0.723	0.125*	1.134	0.126	7.944	0.252	4.509**	158	-2.123*
CDM	893	1.51	0.337	0.047	0.113	0.082	3.965	0.163	5.065**	433	1.261
CIH	1186	1.13	0.120	0.083**	-0.066	0.071	1.980	0.142	5.662**	573	0.404
CLT	540	2.49	0.599	0.053	0.652	0.105	8.068	0.210	5.147**	217	-2.497*
CMA	922	1.46	0.316	0.142**	-0.243	0.081	29.400	0.161	5.459**	397	-2.029*
CRD	1033	1.30	0.234	0.118**	-0.670	0.076	4.728	0.152	5.298**	483	0.177
CSR	729	1.84	0.459	-0.023	0.121	0.091	2.747	0.181	4.936**	323	-1.545
CTM	1171	1.15	0.131	0.104**	-0.036	0.071	3.613	0.143	6.524**	484	-0.919
DIS	587	2.28	0.564	0.149**	2.192	0.101	18.590	0.201	5.562**	251	-1.371
EQD	1154	1.17	0.144	0.062*	-0.227	0.072	25.577	0.144	5.341**	524	-2.062*
FRT	964	1.40	0.285	0.167**	0.624	0.079	6.525	0.157	4.884**	463	2.096*
GTM	656	1.52	0.513	0.223**	-0.175	0.095	2.761	0.191	4.480**	313	0.641
HOL	1261	1.07	0.064	0.099**	-0.662	0.069	24.585	0.138	5.526**	535	-3.594**
LES	625	2.15	0.536	0.084*	-0.045	0.098	4.950	0.195	4.508**	268	-1.59
LGT	600	2.25	0.554	0.156**	-0.195	0.100	2.061	0.199	4.115**	269	-1.571
ONA	1334	1.01	0.010	0.036	0.301	0.067	9.065	0.134	5.090**	577	-3.719**
OUL	411	3.04	0.695	0.115*	0.042	0.120	4.788	0.240	3.199**	168	-2.913**
SBM	935	1.44	0.306	0.162**	-0.139	0.080	8.487	0.160	6.020**	378	-4.259**
SID	1308	1.03	0.030	0.053	0.037	0.068	22.475	0.135	4.776**	589	-2.438*
SNI	1322	1.02	0.019	0.000	0.306	0.067	6.381	0.134	4.979**	545	-4.525**
SOF	425	2.92	0.684	0.160**	0.166	0.118	3.578	0.236	4.424**	163	-1.324
WFB	1304	1.03	0.033	0.045	0.221	0.068	8.056	0.135	4.545**	574	-3.548**

* Implies significance at the 5% level (2-tailed).
** Implies significance at the 1% level (2-tailed).
[r] Correlations between unadjusted TOT returns and the number of days between trades (i.e. one plus the duration of nontrading)
[s] All the Kolmogorov-Smirnov Z statistics were significant at less than the 1% level (2-tailed)
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

For Morocco, all (except one) coefficients are positive. Of these, 12 are significant at the 1% level and 4 at the 5% level. Unlike in the Kenyan case, the only stock (CSR) with a negative coefficient of -0.023 (see Table 5.5, column 5) is not an actively traded stock. In fact it has a thin trading frequency of 45.9 percent and an average number of days between trades of 1.84 days. Therefore this negative relationship could be a result of the news effects cancelling out as explained earlier on.

Table 5.6: Zimbabwe – Thin trading, correlations between TOT returns in absolute terms and the number of days between trades, normality tests and the runs test for TOT-adjusted returns

Stock		Thin trading (a)		(b)[r]	Normality Tests (c)					Runs Test (d)	
	No. of Observations	Ave.# days between trades	Proportion of non-traded days	Spearman's Rank Correlations	Skewness	Std. Err.	Kurtosis	Std. Err.	Kolmogorov -Smirnov Z	No. of Runs	Z-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)[s]	(10)	(11)
APEX	504	2.68	0.627	0.273**	1.403	0.109	19.997	0.217	4.507**	187	-1.427
ARIS	687	1.97	0.492	0.249**	-0.319	0.093	9.208	0.186	5.740**	258	0.221
BARC	1293	1.05	0.044	0.137**	-1.127	0.068	25.346	0.136	8.791**	373	-6.158**
BICC	361	3.74	0.732	0.305**	-1.630	0.128	18.270	0.256	4.103**	141	0.687
BIND	761	1.77	0.437	0.199**	-1.242	0.089	22.417	0.177	5.943**	272	-1.728
CAPS	758	1.78	0.439	0.128**	-2.751	0.089	49.675	0.177	5.054**	293	-1.435
CLAN	690	1.96	0.489	0.211**	0.172	0.093	7.147	0.186	6.130**	257	-0.127
COLC	940	1.44	0.305	0.247**	-0.282	0.080	9.201	0.159	6.489**	337	-2.943**
DELT	1263	1.07	0.066	0.130**	0.473	0.069	10.726	0.138	7.729**	398	-6.316**
DWHI	729	1.85	0.460	0.148**	2.172	0.091	23.821	0.181	6.035**	321	1.815
EDGA	885	1.53	0.345	0.271**	-0.257	0.082	8.402	0.164	6.524**	292	-3.881**
FALG	719	1.88	0.468	0.293**	-2.965	0.091	44.858	0.182	6.221**	285	0.424
FINH	570	2.37	0.578	0.273**	-1.233	0.102	14.562	0.204	4.911**	198	-2.955**
GULL	455	2.96	0.663	0.300**	0.902	0.114	10.258	0.228	4.002**	175	0.921
HIPP	725	1.86	0.463	0.283**	2.479	0.091	30.800	0.181	6.198**	247	-1.884
HUNY	847	1.57	0.373	0.274**	1.233	0.084	10.093	0.168	6.609**	336	0.400
KING	1161	1.16	0.141	0.093**	1.023	0.072	14.431	0.143	6.685**	417	-3.904**
MEIK	957	1.41	0.292	0.217**	1.812	0.079	21.161	0.158	6.365**	313	-5.140**
NATF	408	3.31	0.698	0.263**	0.430	0.121	11.359	0.241	4.363**	145	-0.244
PGI	879	1.54	0.350	0.200**	0.524	0.082	9.414	0.165	5.574**	335	-1.701
RADA	519	2.60	0.616	0.280**	0.521	0.107	18.707	0.214	4.566**	207	-0.692
RIO	478	2.82	0.646	0.362**	-0.795	0.112	12.537	0.223	5.097**	166	-2.122*
SEED	1019	1.33	0.246	0.209**	2.311	0.077	31.651	0.153	6.623**	353	-3.682**
TA	947	1.43	0.299	0.190**	-0.119	0.079	8.385	0.159	7.085**	325	-2.147*
TANG	575	2.35	0.574	0.325**	2.584	0.102	21.207	0.203	4.886**	165	-3.886**
TEDC	805	1.68	0.404	0.193**	-0.650	0.086	18.030	0.172	6.826**	269	-2.464*
TRUW	613	2.21	0.546	0.280**	-2.101	0.099	39.539	0.197	4.777**	242	-0.386
TSL	660	2.05	0.511	0.280**	1.122	0.095	13.308	0.190	4.784**	258	-2.142*
WCOL	924	1.46	0.316	0.161**	-1.916	0.080	40.114	0.161	7.265**	297	-4.583**
ZPAP	997	1.36	0.262	0.208**	-1.642	0.077	27.205	0.155	7.250**	385	-0.639
ZSUN	947	1.43	0.299	0.199**	-1.684	0.079	15.564	0.159	7.608**	347	-0.642

* Implies significance at the 5% level (2-tailed).
** Implies significance at the 1% level (2-tailed).
[r] Correlations between unadjusted TOT returns and the number of days between trades (i.e. one plus the duration of nontrading)
[s] All the Kolmogorov-Smirnov Z statistics were significant at less than the 1% level (2-tailed)
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

On the Zimbabwe Stock Exchange, all the 31 stocks show a strong positive relationship between the absolute returns and the number of days between trades (correlation coefficients are positive and significant at the 1% level) (see Table 5.6, column 5). This is so despite the trading frequencies of the stocks, whether actively traded or thinly traded. The actively traded stocks for this exchange are the multinational corporations, BARC and DELT, with thin trading frequencies of 4.4 percent and 6.6 percent respectively and average number of days between trades of 1.04 and 1.07 days respectively. The explanation could be that on this market, reports of good (bad) news tend to be followed by reports of good (bad) news. Thin trading is also very high on this market. Apart from the two stocks, BARC and DELT, the rest of the stocks in the sample have thin trading frequencies of more than 10 percent.

The evidence thus provided here shows that there is a positive relationship between the number of days between trades, (or rather the duration of nontrading), and the size of the return. Where the relationship is weak or negative, it is because of the composition of information that is being incorporated in a once-off adjustment. If the composite information is a mixture of both bad and good news, then the ultimate effect (positive or negative returns) and the size of the returns will depend on the overriding information. Actually the findings presented here show that thin trading creates a pattern in returns that investors can exploit or use to predict future returns. Even if the stock will adjust for all the information at some point in time, some information will be adjusted with a lag and it is this lagged response that provides an opportunity for smart investors.

The remaining analysis is based on adjusted TOT returns obtained using equation (5.11). The effect of the irregular return intervals resulting from thin trading is adjusted for by weighting the TOT returns by the number of days between trades.

5.5.2 The normality assumption

Bekaert and Harvey (2002) highlighted that emerging market returns are not normally distributed, but are skewed and have fat tails. Fama (1965), using 30 stocks of the Dow Jones Industrial Average, also proved correct the Mandelbrot hypothesis that the stable Paretian distribution is a more appropriate distribution for stock price changes than the normal.

The normality assumption enables the derivation of the probability or sampling distributions. Use of the t and F statistics also require that the error terms or increments follow the normal distribution. Tests for normality include the Jarque-Bera (JB) test, which is an asymptotic or large sample test. Other tests for normality now found on most computer statistical software include the Kolmogorov-Smirnov test, the Lilliefors test and the Shapiro-Wilk test. Besides these tests one can also make use of the skewness and kurtosis values, that is the third and fourth moments results, which under the normal distribution are expected to be zero and 3, respectively. Skewness measures the symmetric properties of the distribution while kurtosis measures its peakedness.

In the current study, the normality assumption is rejected in all the stocks on all the four stock markets at less than the 1% level of significance using the one sample Kolmogorov-Smirnov (K-S) Z normality test. The only stock that rejects normality at a higher level of significance (5%) is NBDV of Egypt. Even though the Shapiro-Wilk test is considered much stronger than the K-S test, its tendency is to increase the chances of rejection of normality and since normality is already rejected using the weaker K-S test, there is no need to seek a stronger test statistic.

The deviation from normality is not surprising as it has been empirically proven even in theory, but it is the extent of that deviation that is of interest. The stable Paretian distribution suggested in theory is a broad categorisation of distributions, which includes even those distributions with infinite variance. The construct of these distributions is that a sum of stable random variables is also a stable random variable. Given that the variables are non-normal, the tendency is to have more probability mass in the tail ends or fat long tails and in some cases the distributions are more peaked than under normality. This can also be explained using the statistics on skewness and kurtosis summarised in Table 5.7.

Table 5.7: Number of stocks with (in) significant skewness and kurtosis at the 5% level of significance

Country/stock exchange	Skewness				Kurtosis			
	Significant		Insignificant		Significant		Insignificant	
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
Egypt	14	16	15	9	42	8	3	1
Kenya	9	14	3	4	30	-	-	-
Morocco	10	4	6	6	26	-	-	-
Zimbabwe	14	15	1	1	31	-	-	-

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Table 5.3, column 6, and Table 5.7, show that for Egypt, 30 of the 54 stocks have skewness significantly different from zero, and of these, 16 exhibit negative skewness, that is, long left tails, while 14 exhibit positive skewness, that is, long right tails. This shows that the distributions of these stocks' returns are, contrary to normality, asymmetrical. While the remaining stocks have skewness not significantly different from zero, nine are skewed to the left, while 15 are skewed to the right. The statistics for kurtosis on Egyptian stocks (Table 5.3, column 8, and Table 5.7) shows that four of the stocks have kurtosis not significantly different from zero, one negative and three positive. Of those significantly different from zero, 42 are positive and eight are negative. This means that the former has more observations clustered in the centre of the distribution and longer tails than the normal distribution while the latter has less clustered observations and shorter tails than under normality. Considering both the skewness and kurtosis, Egypt has three stocks close to normality as evidenced by the insignificance of both the skewness and kurtosis i.e. ELSG, INEG and SGEN.

Kenya also shows nine stocks with positive skewness and 14 stocks with negative skewness, all significantly different from zero and thus long right and left tails respectively. Of the remaining seven stocks with skewness insignificantly different from zero, 4 have negative while 3 have positive skewness (see Table 5.4, column 6, and Table 5.7). In Morocco, four stocks exhibit significant negative skewness while 10 exhibit significant positive skewness. The remaining 12 are evenly distributed with 6 having negative but insignificant skewness and six with positive though insignificant skewness. On the Zimbabwe Stock Exchange, only two have skewness insignificantly different from zero (one positive and one negative) while 15 have negative skewness and 14 have positive skewness all significantly different from zero. The kurtosis for all the Kenyan, Moroccan and Zimbabwean stocks are positive and significantly different from zero at the 5% level. This means that the stock returns are highly concentrated on the centre of the distribution (leptokurtic) with long fat tails as compared to the normal distribution. Therefore all the sample stocks for these markets deviate from the normality assumption.

The deviation from normality is a serious problem that should not be overlooked. It also needs to be emphasised that the appropriate testing methods, given this evidence, should be nonparametric methods, as they do not assume any specific distribution. If the series satisfy the normality assumption or at least approximate it, then the method used will not matter much. In the event of significant deviation from normality, a nonparametric measure is more appropriate. In emerging markets, African markets to be more specific, non-parametric methods are highly recommended.

In the following section, although both the parametric (serial correlation) and nonparametric (runs test) methods are used and results for both are presented, conclusions on randomness are based on the runs tests. The serial correlation test helps in detecting the presence of higher-order serial correlation, which is difficult to detect by merely using the runs rest.

5.5.3 Random walk

5.5.3.1 <u>Serial correlation</u>

The partial autocorrelation coefficient function (PACF) results (see Tables 5.8 to 5.11) shows some dependency in stock returns for the first lag in 39 out of 54 stocks for Egypt; 20 out of 30 stocks for Kenya; 13 out of 27 stocks for Morocco; and 16 out of 31 stocks for Zimbabwe.

Lag 1 tells us to what extent today's return helps in predicting the return for the next trade. The magnitude of dependency is, however, quite small for all the stocks and in particular for stocks in Morocco and Zimbabwe with the largest coefficients in absolute values being 0.197 and 0.173 respectively as compared to the highest of 0.445 and 0.353 for Egypt and Kenya respectively.

Considering the signs of the coefficients for lag 1, the majority of stocks (50/54) for Egypt are positive while of the 4 that are negative only one is twice its standard error (that is, significant at the 5% level). Though not to the same extent, the picture is similar for Zimbabwe with 23/31 stocks having positive autocorrelation coefficients against 8 negatives of which only 2 are significant. For the positive coefficients, 14 are significant at the 5% level.

For Kenya, the pattern is different. There are more stocks with negative coefficients for lag 1 (24/30) than with positive coefficients. For those with positive coefficients only one is significant while for those with negative coefficients, 19 are significant at the 5% level. The preponderance of negative coefficients is also evident in Moroccan stocks with 16 out of 27 stocks exhibiting negative coefficients of which 10 are significant as compared to 10 positive coefficients with only three significant at the 5% level. The results are also summarised in Table 5.12.

Table 5.8: Partial autocorrelation coefficients (Egypt)

Stock	std. err	Lag 1	2	3	4	5	6	7	8	9	10
ALXP	*0.05*	0.055	0.116*	0.026	0	0.052	-0.002	-0.002	0.06	-0.032	0.1*
ALXW	*0.035*	0.234*	0.158*	0.013	0.079*	0.014	0.004	0.061	0.04	0.012	0.013
AISC	*0.042*	0.082	0.162*	0.046	-0.03	-0.028	-0.018	0.045	-0.053	-0.081	-0.015
APCC	*0.029*	0.062*	0.013	0.004	-0.02	-0.004	-0.012	-0.03	0.043	0.056	0.019
ABCE	*0.043*	0.188*	0.085	0.054	0.015	0.007	-0.002	-0.019	0.024	-0.011	0.037
CAPL	*0.043*	0.227*	0.092*	-0.008	-0.07	-0.036	-0.093*	-0.104*	-0.008	-0.007	-0.062
CIB	*0.028*	0.085*	-0.088*	0.022	-0.01	0.005	-0.012	0.019	-0.009	0.024	0.021
DLNS	*0.042*	0.044	0.161*	-0.004	-0.01	-0.019	-0.066	0.002	0.028	-0.014	-0.024
EAB	*0.028*	0.234*	-0.011	-0.036	-0.02	0.016	-0.019	-0.016	-0.062*	0.028	0.023
EDLT	*0.028*	0.026	-0.046	-0.036	-0.04	-0.01	-0.05	0.033	0.007	0.073*	0.048
EDBK	*0.029*	0.023	-0.102*	-0.007	-0.02	-0.019	-0.023	0.01	-0.012	0.03	-0.02
EFIN	*0.029*	0.077*	-0.108*	0.013	-0	0.011	-0.028	-0.007	-0.004	0.018	0.018
EGCM	*0.04*	0.096*	-0.02	0.029	-0.04	0.007	-0.026	0.01	0.043	0.051	-0.047
EGSR	*0.033*	0.028	0.027	-0.006	0.042	-0.006	0.036	0.041	0.024	0.032	0.037
ECAB	*0.028*	0.063*	-0.108*	-0.031	-0.03	0.032	-0.02	-0.017	0.018	0.012	0.023
ELKA	*0.028*	0.147*	-0.05	0.014	0.052	0.014	0.017	0.039	0.04	0.016	-0.012
ELND	*0.039*	0.133*	0.056	-0.049	0.022	0.055	0.01	-0.03	-0.06	0.037	-0.024
ELSG	*0.051*	0.184*	0.083	0.045	0.066	-0.05	-0.007	0.01	-0.13*	0.022	-0.046
EWBK	*0.028*	0.051	-0.038	-0.005	0.012	-0.009	0.006	0.032	-0.048	0.004	-0.015
ETBC	*0.028*	0.141*	-0.013	-0.024	0.049	-0.012	-0.016	0.039	0.026	0.017	0.031
EXOL	*0.037*	0.112*	0.051	0.031	-0.07	0.029	-0.074*	0.01	0.037	0.029	0.007
HHSE	*0.035*	0.171*	0.04	-0.042	-0.05	0.017	-0.039	-0.001	-0.026	-0.006	0.022
HCST	*0.045*	0.445*	0.142*	-0.01	0.002	-0.015	-0.044	-0.002	-0.163*	0.064	-0.085
HPCC	*0.029*	0.119*	-0.032	0.021	0.041	0.048	0.005	-0.008	0.002	0.04	-0.007
INEG	*0.036*	0.15*	0.055	0	-0.09*	-0.055	-0.023	-0.021	0.005	0.001	-0.002
KZAY	*0.032*	0.033	0.06	-0.004	-0.01	-0.05	0.01	-0.057	-0.052	0.007	0.011
MPHS	*0.04*	-0.039	-0.008	0.037	-0.09*	-0.035	0.033	-0.015	-0.008	-0.035	0.03
MIBK	*0.028*	0.119*	-0.043	-0.016	-0.04	0.02	-0.035	0.019	-0.049	-0.011	-0.034
MDGM	*0.028*	0.03	-0.079*	-0.024	0.019	0.028	-0.003	0.006	-0.011	0.038	0.035
MWST	*0.028*	-0.044	-0.022	-0.028	-0.05	0.027	-0.014	-0.018	-0.014	0.009	0.024
MSCM	*0.028*	0.207*	-0.057*	0.005	0.021	0.007	0.061*	-0.035	-0.065*	-0.019	-0.011
MHOT	*0.03*	0.115*	0.003	0.017	0.021	-0.019	-0.059	0.001	-0.007	-0.001	-0.026
MOIL	*0.043*	-0.045	-0.032	-0.046	-0.01	-0.039	0.045	0.018	-0.019	0.026	-0.025
MHBK	*0.035*	0.114*	-0.029	-0.04	-0.09*	0.015	-0.068	0.027	0.017	-0.025	-0.088*
MHIN	*0.04*	0.209*	-0.005	0.034	-0.06	0.08*	-0.082*	0.015	-0.037	0.017	-0.021
NTCM	*0.031*	0.251*	0.032	0.008	0.015	-0.009	-0.021	-0.022	-0.003	0.015	0.01
NBDV	*0.029*	0.137*	0.09*	0.025	-0.05	-0.016	-0.029	-0.016	-0.039	-0.019	-0.025
NCAI	*0.029*	0.109*	-0.011	-0.035	0.008	0.017	0.04	-0.054	0.047	-0.012	0.008
NLMT	*0.029*	0.031	-0.065*	-0.071*	-0.04	-0.04	-0.025	-0.051	-0.024	0.012	-0.035
NLPM	*0.039*	0.091*	-0.013	-0.012	-0.06	0.063	0.001	-0.024	0.003	0.016	-0.005
NCTY	*0.028*	0.179*	-0.031	0.002	0.009	0.007	0.005	-0.018	-0.004	0.052	0.019
NSGB	*0.029*	0.009	-0.108*	-0.021	-0.08*	0.017	0.002	-0.045	-0.031	0.017	0.047
ORNT	*0.054*	0.214*	0.185*	0.067	0.032	-0.057	-0.077	-0.082	-0.066	-0.11*	0.081
PCHC	*0.028*	0.025	-0.083*	0.006	0.057*	-0.002	0.006	-0.012	-0.013	-0.009	0.014
PFIZ	*0.03*	0.221*	0.031	0.03	0.008	-0.021	-0.039	0.013	-0.007	0.019	0.073*
RKTA	*0.037*	0.268*	0.031	0.016	0.001	-0.018	-0.009	0.013	-0.012	0.013	-0.008
SCAI	*0.029*	0.104*	-0.025	-0.051	0.043	0.042	-0.011	0.005	0.032	0.034	-0.009
SGEN	*0.051*	0.31*	0.102*	0.014	0.03	0.047	0.052	0.099	-0.077	-0.022	-0.016
SZCN	*0.033*	-0.112*	0.085*	0.04	-0.04	-0.063	-0.116*	0.01	-0.078*	0.014	0.027
SZCM	*0.028*	0.068*	-0.08*	0.01	-0.02	-0.04	-0.054	0.018	-0.023	0.009	0.02
TORA	*0.028*	0.118*	-0.053	0.065*	-0.01	0.025	0.055	0.014	-0.041	-0.032	0.014
UHDV	*0.03*	0.075*	-0.059	-0.088*	-0.07*	-0.058	-0.038	-0.03	0.016	0.029	0.011
UPAC	*0.043*	0.305*	0.138*	0.028	-0.02	0.01	-0.035	-0.044	0.023	-0.031	-0.026
UPGL	*0.028*	0.108*	-0.107*	0.006	-0.02	-0.037	-0.017	-0.01	0.011	0.005	0.077*

*Coefficient is twice its computed standard error
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Table 5.9: Partial autocorrelation coefficients (Kenya)

Stock	std. err	Lag 1	2	3	4	5	6	7	8	9	10
BAM	*0.036*	-0.103*	-0.006	-0.025	-0.09*	0.028	0.022	-0.014	-0.008	0.039	0.007
BAT	*0.031*	-0.353*	-0.032	0.073*	0.03	0.013	-0.037	-0.005	-0.031	-0.052	0.03
BBK	*0.027*	-0.156*	0.029	0.018	-0.029	-0.033	0.05	0.026	-0.005	-0.038	-0.088*
BBD	*0.04*	-0.136*	-0.001	0.019	0.011	-0.023	0.009	0.033	0.007	-0.025	-0.08*
CRB	*0.052*	-0.12*	0.035	0.031	0.041	0.003	-0.097	-0.058	-0.02	0.077	0.032
CBG	*0.041*	-0.184*	0.125*	0.035	-0.004	-0.03	-0.008	-0.035	0.032	-0.004	-0.027
CFC	*0.041*	-0.14*	-0.004	0.015	0.058	-0.023	-0.019	-0.004	-0.016	-0.033	0.034
CMC	*0.047*	-0.088	0.009	0.073	0.11*	0.063	-0.004	-0.009	0.001	0.041	0.075
DTK	*0.037*	-0.157*	-0.03	-0.088*	-0.041	-0.034	-0.015	-0.05	-0.056	0.023	0.003
EBL	*0.029*	-0.207*	-0.007	0	-0.056	-0.032	0.026	-0.023	-0.009	0.001	0.016
ECB	*0.052*	0.01	-0.028	0.198*	0.031	-0.084	-0.036	-0.049	0.012	-0.01	0.033
FST	*0.032*	-0.093*	0.035	0.002	0.009	0.035	-0.036	-0.004	0.023	0.015	-0.085*
GWK	*0.05*	0.024	0.1*	0.071	-0.002	0.058	0.009	0.046	0.009	0.002	-0.066
HFC	*0.029*	-0.285*	-0.077*	-0.02	0.012	0.049	0.042	-0.028	-0.008	0.017	-0.03
ECD	*0.03*	-0.152*	-0.017	0.129*	-0.008	-0.005	-0.021	0.016	-0.016	0.037	-0.016
JUB	*0.037*	-0.162*	-0.025	0.046	-0.029	-0.006	-0.054	-0.041	-0.062	0.018	-0.02
KCB	*0.027*	-0.048	0.057*	0.009	-0.017	-0.01	0.022	-0.012	-0.043	0.022	-0.004
KNL	*0.054*	-0.029	0.01	0.029	-0.028	0.032	0.002	-0.079	0.086	-0.021	-0.03
KNM	*0.037*	-0.056	0	0.053	0.019	-0.045	0.032	-0.018	-0.008	-0.039	0.045
KPL	*0.03*	0.024	-0.005	0.048	0.01	0.047	0.014	0.097*	0.005	0.007	-0.011
NBK	*0.028*	-0.119*	-0.057*	0.018	-0.048	0.052	-0.061*	-0.041	-0.029	-0.023	-0.025
NIC	*0.028*	-0.273*	0.021	0.048	0.005	-0.009	-0.014	0.013	0.018	-0.04	0.027
NMG	*0.029*	-0.068*	-0.05	-0.039	-0.069*	-0.022	0.017	0.007	0.015	-0.01	0.066*
RVP	*0.033*	-0.2*	-0.056	-0.039	0.001	-0.028	-0.049	-0.051	-0.05	-0.021	-0.032
SSN	*0.042*	-0.069	-0.065	-0.007	-0.053	0.214*	-0.1*	0.04	-0.053	0.052	0.095*
SBK	*0.027*	-0.123*	0.037	0.019	0	-0.028	-0.051	-0.052	-0.031	-0.002	-0.01
SNG	*0.046*	0.098*	0.02	-0.017	-0.053	0.07	0.098*	0.03	-0.081	-0.02	0.066
TTL	*0.034*	0.028	-0.004	0.019	-0.026	0.057	0.02	0.015	-0.005	-0.022	-0.035
UCH	*0.029*	-0.349*	-0.108*	-0.03	-0.016	0.038	0.035	-0.012	0.012	-0.042	0.018
UNG	*0.039*	0.011	-0.021	0.049	0.032	-0.007	0.044	0.009	0.029	-0.018	-0.082*

*Coefficient is twice its computed standard error

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Table 5.10: Partial autocorrelation coefficients (Morocco)

Stock	std. err	Lag 1	2	3	4	5	6	7	8	9	10
ATH	*0.053*	-0.072	0.058	-0.012	0.084	0.051	0.035	-0.04	0.082	-0.131*	-0.072
BCE	*0.027*	0.032	0.076*	-0.094*	-0.054*	-0.039	-0.007	-0.02	0.059*	0.007	0.027
BCI	*0.03*	-0.028	0.071*	0.07*	-0.09*	0.009	0.042	-0.01	0.041	-0.049	-0.021
BCM	*0.028*	-0.036	-0.036	-0.011	-0.019	-0.051	-0.047	0.027	0.006	-0.012	0.011
BDE	*0.03*	-0.124*	-0.01	-0.075*	-0.064*	0.008	-0.01	-0.01	0.028	-0.002	0.035
BNM	*0.052*	-0.061	0.023	0.131*	0.01	0.018	0.098	-0.06	0.075	-0.04	-0.029
CDM	*0.033*	-0.078*	0.01	0.004	-0.03	-0.059	-0.048	-0.03	-0.09*	0.03	-0.033
CIH	*0.029*	-0.106*	0.003	-0.031	0.017	-0.053	0.004	0.041	-0.02	0.051	0.022
CLT	*0.043*	0.062	-0.033	0.046	0.007	0.08	-0.039	0.011	0.045	0.022	-0.049
CMA	*0.033*	-0.082*	-0.004	0.037	0.025	-0.01	0.017	0.008	0.002	-0.026	-0.049
CRD	*0.031*	-0.108*	0.068*	0.034	-0.056	0.05	-0.009	0.035	0.032	0.007	0.032
CSR	*0.037*	-0.035	0.009	0.015	0.034	-0.035	-0.054	-0.05	-0	0.022	-0.048
CTM	*0.029*	-0.009	-0.015	0.008	-0.025	-0.017	-0.005	-0.04	-0.06*	-0.021	-0.046
DIS	*0.041*	0.022	0.03	0.087*	0.001	0.014	0.043	-0.02	0.078	0.032	0.036
EQD	*0.029*	-0.138*	0.016	0.019	0.012	-0.034	0.035	0.055	-0.02	0.013	-0.039
FRT	*0.032*	-0.197*	-0.099*	0	-0.001	0.026	-0.021	-0.02	-0.01	0.025	-0.006
GTM	*0.039*	-0.14*	-0.032	0.012	-0.006	-0.091*	-0.064	-0.05	-0.14*	-0.006	-0.023
HOL	*0.028*	0.008	0.047	0	0.031	-0.011	0.043	-0	0.069*	0.014	0.036
LES	*0.04*	-0.13*	0	0.014	-0.079	0.036	0.004	0.022	-0.03	-0.02	-0.039
LGT	*0.041*	0.104*	0.004	-0.001	0.031	0.117*	-0.028	-0.05	0.019	0.031	0.051
ONA	*0.027*	0.114*	0.027	-0.099*	-0.019	-0.029	0.013	0.035	-0	-0.002	0.03
OUL	*0.049*	0.026	-0.016	0.012	0.082	-0.001	-0.024	-0.01	-0.09	0.04	0.029
SBM	*0.033*	0.007	0.039	0.089*	0.03	0.105*	-0.024	-0.03	0.029	-0.001	-0.016
SID	*0.028*	-0.065*	0.016	-0.007	-0.004	-0.025	0	0.01	0.002	0.021	0.038
SNI	*0.028*	0.12*	-0.09*	-0.005	-0.071*	-0.017	-0.054	0.018	0.019	-0.033	-0.002
SOF	*0.049*	0.075	-0.004	0.025	-0.009	-0.06	0.03	-0.03	0.073	0.029	-0.112*
WFB	*0.028*	0	0.039	0.002	-0.07*	0.008	-0.008	-0.01	0.03	-0.011	-0.002

*Coefficient is twice its computed standard error

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Table 5.11: Partial autocorrelation coefficients (Zimbabwe)

Stock	Std. err	Lag 1	2	3	4	5	6	7	8	9	10
APEX	*0.045*	-0.073	-0.002	0.063	0	-0.016	0.04	-0.042	0.049	0.022	-0.033
ARIS	*0.038*	0.037	0.051	-0.007	0.048	0.029	0.003	0.002	-0.006	0.02	-0.033
BARC	*0.028*	0.106*	-0.002	-0.034	0.039	-0.083*	-0.064*	0.001	0.005	0.01	-0.029
BICC	*0.053*	0.051	0.046	0.005	-0.023	0.126*	0.025	0.075	-0.024	0.029	-0.09
BIND	*0.036*	0.106*	-0.078*	-0.039	-0.008	0.05	0.03	0.01	-0.007	-0.048	-0.018
CAPS	*0.036*	0.074*	0.042	-0.041	0.009	0.001	-0.002	0.018	0.02	0.091*	-0.092*
CLAN	*0.038*	-0.075	-0.097*	-0.031	-0.026	-0.002	0.014	-0.066	-0.051	-0.003	-0.063
COLC	*0.033*	0.11*	0.002	0.023	0.003	0.016	-0.005	0.012	-0.004	0.005	-0.054
DELT	*0.028*	0.073*	0.007	0.046	-0.011	-0.105*	0.069*	-0.018	-0.003	-0.014	0.005
DWHI	*0.037*	-0.106*	-0.026	-0.107*	-0.121*	-0.028	0	0.001	0.011	-0.005	0.043
EDGA	*0.034*	0.073*	0.046	0.018	0.017	0.038	0.018	-0.012	0.041	-0.021	-0.085*
FALG	*0.037*	-0.107*	-0.112*	-0.058	0.007	0.04	-0.046	0.039	-0.007	0.029	0.014
FINH	*0.042*	0.077	0.077	-0.075	-0.069	-0.115*	0.043	0.006	-0.01	-0.038	-0.016
GULL	*0.047*	-0.075	0.059	0.025	0.019	-0.025	-0.027	0.001	-0.053	-0.022	-0.024
HIPP	*0.037*	-0.032	0.04	0.014	0.031	0.002	-0.001	-0.031	-0.039	0.018	0.033
HUNY	*0.034*	-0.04	0.032	0.011	-0.004	-0.039	0.05	-0.01	-0.054	0.044	-0.041
KING	*0.029*	0.173*	-0.085*	0.011	-0.012	-0.027	-0.006	0.016	-0.059*	-0.023	0.028
MEIK	*0.032*	0.141*	-0.064*	0	-0.04	-0.005	-0.023	0.02	0.041	-0.057	-0.007
NATF	*0.05*	0.141*	0.048	-0.01	-0.054	0.006	-0.028	0.003	-0.039	-0.026	0.011
PGI	*0.034*	0.017	-0.043	-0.097*	-0.1*	-0.068*	0.041	-0.025	0.001	0.034	0.037
RADA	*0.044*	0.075	-0.059	-0.024	0.005	-0.022	0.075	0.01	-0.059	0.033	-0.02
RIO	*0.046*	0.125*	-0.024	-0.089	0.018	0.058	-0.094*	-0.031	-0.079	0.061	0.012
SEED	*0.031*	0.137*	0.01	0.034	0.03	0.011	-0.032	-0.002	0.016	0.062*	-0.011
TA	*0.032*	0.097*	-0.008	-0.116*	-0.021	-0.041	0.007	-0.007	-0.001	-0.011	0.013
TANG	*0.042*	0.068	0.026	0.038	0.018	0.023	-0.013	0.01	-0.009	-0.015	-0.011
TEDC	*0.035*	0.09*	-0.068	-0.056	0.072*	-0.044	0.086*	0.033	-0.113*	-0.058	0.091*
TRUW	*0.04*	0.017	0.018	-0.021	-0.021	0.003	-0.024	-0.036	-0.036	0.041	-0.048
TSL	*0.039*	0.163*	-0.009	-0.023	0.009	-0.002	-0.035	-0.104*	-0.036	0.027	-0.006
WCOL	*0.033*	0.059	-0.031	-0.171*	-0.074*	-0.018	-0.013	0.009	0.016	0.004	0.041
ZPAP	*0.032*	0.023	-0.062	-0.013	-0.075*	-0.063	-0.011	-0.021	-0.023	-0.004	0.017
ZSUN	*0.032*	-0.023	0.088*	-0.023	-0.094*	-0.007	0.013	0.035	-0.004	0	0.007

*Coefficient is twice its computed standard error
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Table 5.12: First order serial correlation coefficients

Country/ Stock Exchange	PACF: Lag 1 @ 5% level of significance						
	Significant			Insignificant			Correlation tendency
	Positive	Negative	Total	Positive	Negative	Total	
Egypt	38	1	39	12	3	15	Positive
Kenya	1	19	20	5	5	10	Negative
Morocco	3	10	13	7	5	12	Negative
Zimbabwe	14	2	16	9	6	15	Positive

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

It is important to note the presence of higher order serial correlation in returns. Egypt has 22 stocks with significant second order serial correlation coefficients while Kenya and Zimbabwe each have 6 stocks and Morocco has 5 stocks with significant second order coefficients. This means that information about the returns in the past two trades can be used to predict returns in today's trade.

The PACF is, however, a parametric measure and assumes the normal distribution, a condition that has not been satisfied in the return series. The standard errors are thus quite small and the fact that these are used to decide on the rejection or acceptance of the significance of the autocorrelation coefficients leaves a lot to be desired. This resulted in the use of the more robust nonparametric runs test.

5.5.3.2 Runs test

Table 5.3, columns 11 and 12, shows that for Egypt, 28/54 stocks have the actual number of runs significantly different from the expected number of runs, 20 at the 1% level and 8 at the 5% level of significance. Of these only one has a positive Z-score, implying that the observed number of runs are more than the expected number while the remaining 27 stocks have negative Z-scores (observed number of runs are fewer than expected). Fewer runs than expected indicate positive correlation in stock returns. Therefore the results here are consistent with those from the PACF. The only difference is that with the runs test fewer stocks show this relationship at the required level of significance (5%) as compared to the PACF (27 versus 38). Ignoring the significance of the relationship, 45 out of the 54 stocks have negative Z-scores indicating a positive correlation as compared to 50 stocks under the PACF. Non-normality in returns gives a false impression of serial correlation in stocks when in actual fact that correlation is weak or nonexistent.

For Kenya, there are 11 stocks with the actual or observed number of runs significantly different from the expected number and all of them have positive Z-scores indicating negative correlation in stock returns (see Table 5.4, columns 11 and 12). Of these, 8 are significant at the 1% level while 3 are significant at the 5% level. Overall, 23 out of 30 stocks have positive Z-scores and thus negative serial correlation, though not all of them are significant as compared to 24 out of 30 using the PACF. The results compare well with those from the PACF, where the majority of significant first order correlation coefficients show negative correlation in returns. Just like in the Egyptian case, the number of stocks showing significant correlation coefficients is significantly reduced under the runs test (11 as compared to 20 under the PACF).

Exceptionally for Morocco, there are more stocks (14) with significant correlation under the runs test, 7 at the 1% level and 7 at the 5% level of significance (see Table 5.5, columns 11 and 12), as compared to 13 under the PACF. Of these 14 stocks, 13 have negative Z-scores indicating positive correlation. These results are inconsistent with those found using the PACF where only 3 out of the 13 stocks exhibit significant positive serial correlation at lag 1. Without taking significance into account, 19 stocks have negative Z-scores (positive correlation) as compared to only 10 stocks with positive first order correlation under the PACF. With this inconsistency, we rely more on the runs test results due to the test's robustness.

On the Zimbabwe Stock Exchange (see Table 5.6, columns 11 and 12), 14 stocks have significant negative Z-scores and thus exhibit positive serial correlation, 10 at the 1% level and 4 at the 5% level of significance. Disregarding significance, 25 stocks have negative Z-scores and thus positive serial correlation as compared to 23 stocks under the PACF. The only two stocks exhibiting significant negative serial correlation at lag 1 under the PACF, that is, DWHI and FALG, show insignificant negative serial correlation under the runs test.

Table 5.13: Runs test results – a summary

Country/ Stock exchange	Z-scores at the 5% level of significance						
	Significant			Insignificant			Correlation tendency
	Positive	Negative	Total	Positive	Negative	Total	
Egypt	1	27	28	8	18	26	Positive
Kenya	11	-	11	12	7	19	Negative
Morocco	1	13	14	7	6	13	Positive
Zimbabwe	-	14	14	6	11	17	Positive

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

The runs test results indicates significant positive dependency in returns in half (27) of the stocks in the Egyptian sample, in 13/27 and 14/31 stocks for Morocco and Zimbabwe respectively whilst for Kenya, there is a preponderance of negative dependency (reversals), which is significant at the 5% level in 11 of the 30 stocks. The results are summarised in Table 5.13.

5.6 Conclusion

The empirical evidence supports the hypothesis that returns following a period of nontrading tend to be larger in magnitude than returns following another trading day. Even though the correlation coefficients between absolute TOT returns and the number of days between trades are quite small, they are, in most cases positive and significant at the 5% level suggesting a positive relationship between the two variables. This is expected since returns following a period of nontrading tends to reflect information arriving in the market over a period longer than a day.

Returns on African markets deviate significantly from normality. Therefore even though the serial correlation test will give information on higher order correlation, the results are not reliable as the test relies more on the normality assumption. The runs test, though the confidence bounds are also based on the normal distribution, is more robust as a nonparametric measure.

It can be conlcuded that the random walk is not entirely a true description of the returns behaviour of stocks on these four African markets as almost half of the stocks on each of the markets reject the RWH. In Strebel (1977, 1978)'s terminology, the random walk as the description of stock price behaviour on these four African stock markets is rather a "half truth". However, considering the degree of dependency, this is rather weak such that no trader can expect to increase expected gains by trading on historical price information. There is no reason to attribute this dependency to thin trading since such dependency is not only present in stocks of specific trading frequencies. It seems like the adjustment procedure adopted effectively controlled the bias that thin trading creates in autocorrelation analysis.

There are some shortcomings with the random walk tests adopted here. The serial correlation test only measures linear relationships. Considering the lack of orderliness, the messy and complex nature of African stock markets, nonlinear models could be more appropriate. The runs test is also too rigid in that it only measures the change in sign regardless of the size of the return. It will also be interesting to test for dependency in a pre-sample period and investigate if the dependency found is useful in predicting returns on a post-sample period. It is possible that dependency may exist in one form in a pre-sample period and in a different form in a post-sample period, interrupted, for example, by changes in regimes and the economic environment.

Rejecting the random walk hypothesis, however, does not mean rejection of market efficiency but it gives insight that a pattern exists in the stock returns, which traders can use for profitable gains. It is strongly recommended to use more nonparametric methods that are not dependent on the normality or finite variance assumptions in the testing of efficiency on African markets, methods such as technical trading rules and the artificial neural networks.

6 THE EFFICIENCY OF THE THINLY TRADED AFRICAN STOCK MARKETS

6.1 Introduction

This chapter is an extension of Chapter 5. While in Chapter 5 only the four markets where dividend information was available were included, in this chapter all of the ten markets are examined with 'returns' referring to capital gains only. The reason for excluding cash dividends is the difficulty in accessing dividend information for some of the markets included. Comparisons are, however, made with results from Chapter 5 to determine the impact of omitting the dividend information on the results.

While the EMH has drawn great interest in both the investment and academic circles as evidenced by the vast body of research done around this concept, the bulk of this evidence is still from developed markets in the United States and Europe (Groenewold and Ariff, 1998; Mobarek and Keasey, 2000). Little is known about the efficiency of emerging markets in Africa. The general perception is that stock markets in Africa are not efficient. This stems from the unfavourable market regulations, high trading costs and the kind of investors on these markets. This perception, however, relates more to operational and economic efficiency rather than informational efficiency to which the EMH refers.

This chapter studies the weak-form EMH on African stock markets, by investigating if stock price behaviour on these markets conforms to the random walk, using the serial correlation and runs tests. Since the majority of stocks on the African markets are infrequently traded, returns are calculated on a trade-to-trade basis and adjusted for variability in the interval lengths. This is done by weighting the trade-to-trade returns by the number of days between trades (see Mlambo, *et al.,* 2003).

6.2 Review of methodologies on African markets efficiency

The majority of studies relating to market efficiency on African stock markets have been conducted on the Johannesburg Stock Exchange (JSE). On other African stock markets, published research around this concept is still very scarce. The available evidence is mainly from the use of indices data. This is more so in studies that have included more than one market (e.g. Appiah-Kusi and Menyah, 2003). Atchison, *et al.* (1987, p.111) argued that market index autocorrelation by itself is of limited interest. The knowledge of price-adjustment delays causing this autocorrelation is, however, very significant for the understanding of the price-formation process (Atchison, *et al.,* 1987). Dickinson and Muragu (1994) reiterated the same thought arguing that the evidence from indices, although not without limitations, is of considerable value.

If index autocorrelation is of limited interest, it is more so for African stock markets. This is because indices on these markets are not directly tradable unlike those on developed financial markets. These indices also tend to give equal weight to all stocks, whether actively or thinly traded giving the index an inbuilt thin trading effect. With the exception of a few, these indices are also market capitalisation weighted. The listed companies and thus the constituents of these indices tend to vary greatly in size due to the listing of some multinational and foreign corporations. These corporations are relatively much bigger in terms of market capitalisation in comparison to local companies. The indices and their movements thereof, tend to represent and reflect price changes in a minority of companies, that is, the large market capitalisation stocks.

Past research on individual stocks used either monthly or weekly data rather than daily data. The limiting factor, among others, has been the non-availability of computerised databases (Dickinson and Muragu, 1994). The other argument for using data measured over longer time intervals is the problem of thin trading. Increasing the time interval is argued to reduce the potential biases associated with thin trading (Dickinson and Muragu, 1994). It increases the probability of having at least one trade in the interval. The trade, however, would not necessarily have taken place at the end of the interval and thus the "price age" component. This component of thin trading, though more critical in long time horizons, is usually ignored.

Although some studies on African stock markets have acknowledged the thin trading problem, very few have gone beyond mere acknowledgement of the existence of the problem. The limited studies that tried to address the thin trading problem include Asal (2000) on the Egyptian Stock Exchange and Appiah-Kusi and Menyah (2003) on eleven African stock markets. Both studies used the adjustment method by Miller, *et al.* (1994) for index returns. Kallunki and Martikainen (1997) used the Cohen, *et al.* (1983) adjustment method in the investigation of the effect of price adjustment delays on the covariance-factor structure of daily returns on the thinly traded Finnish stock market.

6.3 Data and methodology

The ten markets studied in this chapter are Egypt, Kenya, Zimbabwe, Morocco, Mauritius, Tunisia, Ghana, Namibia, Botswana and the West African Regional Exchange (Bourse Regionale des Valeurs Mobilieres - BRVM) in Cote d'Ivoire. The data used are daily stock prices and volume traded for individual stocks. The data for Egypt, Kenya, Zimbabwe, Morocco and Mauritius were obtained from DataStream and comparisons were made with samples from the respective stock exchanges and/or stockbrokers (e.g. the Nairobi Stock Exchange for Kenya, Casablanca Stock Exchange for Morocco, BARDNET and Kingdom Stockbrokers for Zimbabwe) to determine reliability and accuracy. For Botswana, Namibia and the BRVM, the data were obtained from the respective stock exchanges while for Ghana and Tunisia at least two sources were consulted. These are Tunisie Valeurs, Tustex and Financiere de Placement et de Gestion (FPG) for Tunisia; Databank and SDC Brokerages for Ghana.

The volume traded data is used to determine the trading frequencies and durations of nontrading of the different stocks. The stocks included in the sample are selected according to the following criteria: the stock has been listed for the entire period under consideration; it has not been part of an acquisition or merger during the period under review; it has not been suspended from trade for a period longer than a week; and it has enough data points to make a meaningful analysis.

The period examined for each market is shown in Table 6.1 below. As can be seen from Table 6.1, (see also Appendix F1), the markets in this study exhibit serious thin trading for the period under investigation. For Namibia, the lowest thin trading frequency was 62 percent[1]. If a thin trading frequency of more than 50 percent is considered to be serious, then all the stocks in the Namibian sample can be said to have serious thin trading. Relatively close to this is Botswana with the lowest thin trading frequency of 34 percent and Mauritius with 14 percent. Interestingly, most of the stocks on the Namibian and Botswana stock exchanges have dual listing on the JSE. Probably, trading in these stocks takes place more on the JSE than on these dual markets. Because the majority of stocks, (68 percent), on the Namibian Stock Exchange (NSX) are dual-listings on the JSE, the NSX is usually not open for trade whenever there is a holiday in South Africa.

Table 6.1: Data and thin trading properties

Stock Exchange	Year Established	Data Sampling period*	# Trading days	Sample size	Sample thin trading frequency			
					range	median	average	std dev
Botswana	1989	23 Mar 98 - 31 May 02	1035	12	34-94%	73%	69%	0.21
BRVM	1998	04 Jan 99 - 31 Dec 02	687	24	03-95%	65%	65%	0.22
Egypt	1888/1903	02 Jan 97 - 31 May 02	1342	54	05-74%	18%	29%	0.24
Ghana	1989	02 Jan 98 - 30 Dec 02	603	20	10-87%	70%	58%	0.25
Kenya	1954	02 Jan 97 - 31 May 02	1366	40	02-97%	53%	49%	0.30
Mauritius	1989	01 Jun 98 - 31 Dec 02	1197	9	14-52%	29%	31%	0.14
Morocco	1929	02 Jan 97 - 31 May 02	1349	36	01-97%	49%	45%	0.33
Namibia	1992	02 Jan 97 - 31 May 02	1341	15	62-98%	87%	85%	0.10
Tunisia	1969	02 Jan 98 - 31 Dec 02	1250	35	02-91%	32%	39%	0.31
Zimbabwe	1896(1946)	02 Jan 97 - 31 May 02	1353	39	04-94%	49%	51%	0.23

Notes: *The variability in the sampling periods is due, among other reasons, to the availability of the data. The BRVM, for example, was established towards the end of 1998 and thus the data series could only start after 1998. Mauritius, though established in 1989, changed to daily trading in 1998 and therefore this period was chosen so as not to distort the data series. The Botswana Stock Exchange only started recording transactions data on a daily basis in March 1998 when it introduced the computerised trading system. A large number of stocks were listed on the Tunisian Stock Exchange after the introduction of electronic trading in 1997 and thus the choice of this starting date. For Ghana it was difficult to access data prior to 1998.
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

[1] Thin trading frequency is measured as the number of days a stock does not trade out of the total number of days the stock exchange was open for trade for the period studied. A thin trading frequency of 62% would imply a stock not trading in 62 out of every 100 trading days.

6.3.1 Trade-to-trade returns

Continuously compounded returns are calculated on a trade-to-trade basis and adjusted for interval variability, following Mlambo, *et al.* (2003)[2] and as in Chapter 5 as follows:

$$\tilde{R}_t = \frac{1}{K_t}\left[\ln P_t - \ln P_{t-K_t}\right] \tag{6.1}$$

where:

$\tilde{R}_t$ is the approximate one-day return after adjusting for the interval effect

P_t is the stock's traded price in period t

P_{t-K_t} is the price of a stock K_t periods in the past

K_t is the length of time between the trade in period t and the previous successive trade

As in Chapter 5, the normality assumption is rejected at the 1% level of significance by almost all the stocks using the Kolmogorov-Smirnov and Shapiro-Wilk tests (see Appendix D). A graphical presentation of the distribution of the stock returns (see Appendix E) shows that most of the stocks are highly leptokurtic and have long fat tails as compared to the normal distribution. Such deviation from normality warrants caution in interpreting results from parametric tests.

6.4 Empirical results

The results (see Appendix F) are presented in order of thin trading for all the stock markets, with the most actively traded stocks at the top of the columns and the most infrequently traded stocks taking the bottom of the columns. This was done to enable a quick inspection of the results and identify differences, if any, between the results of infrequently traded stocks and those of stocks that are frequently traded.

[2] Each trade-to-trade return is 'weighted' by the interval length, which in this case is the number of days between trades. This does not mean getting averages and allocating them to each of the days within a trading period (same/identical returns) as might be incorrectly interpreted. In fact only the day when there was trade is considered and all the days not traded are ignored or left out.

6.4.1 The effect of excluding dividends

Efficiency results, when dividends are included and when excluded in the calculation of returns, are compared. The comparison is done using four markets where dividend information was obtained. Excluding dividends from the returns seemed not to provide significant differences in the results especially when the runs test is used (see Appendix F2). This is probably because dividends are infrequently declared on most African stock markets. Even though a company may report its interim and final results, it is possible that it might not declare any cash dividends. Dividends declaration is also not a frequent event in that it happens, at most, twice a year, as interim and as final dividend, such that the effect is quite small, especially when daily returns are considered.

6.4.2 Serial correlation at lag 1

The null hypothesis that there is no serial correlation in successive trade-to-trade returns is tested at the 5% level of significance against the alternative that serial correlation exists for lags 1 to 10. If the correlation coefficient at lag k is not significantly different from zero, the implication is that there is no serial correlation at this lag. The correlation coefficient is given by:

$$\rho_k = \frac{\operatorname{cov}(\tilde{R}_t, \tilde{R}_{t-k})}{\operatorname{var}(\tilde{R}_t)} \tag{6.2}$$

According to Fama (1965), for a large finite-variance distributed sample, the standard error is given by:

$$\sigma(\rho_k) = 1 \Big/ \sqrt{(n-k)} \tag{6.3}$$

where n is the sample size.

The serial correlation coefficients at lag 1 are the same whether one uses the partial autocorrelation (PACF) or sample autocorrelation (ACF) functions. This is because both correlate the values of a series with its values at lag 1 or greater. However, with the PACF the effect of the information at intervening lags is removed. Therefore since at lag 1, there are no intervening lags, the two functions are bound to give the same results and only to differ at lags greater than 1. The serial correlation test results for lag 1 are summarised in Table 6.2. (See also Appendix F3).

The serial correlation test results show that the majority of stocks indicate positive dependency for the BRVM, Egypt, Ghana, Tunisia and Zimbabwe, and negative dependency for Kenya and Morocco. For Botswana, Mauritius and Namibia, there are no clear correlation patterns. For Botswana, there are an equal number of stocks showing either positive or negative dependency when all stocks are considered. There are, however, only slightly more stocks with negative dependency when only the stocks rejecting the random walk are considered. While there are more stocks for Namibia and Mauritius exhibiting negative correlation tendencies when all stocks are considered, the patterns are reversed when only the stocks rejecting the random walk are considered.

Table 6.2 shows that more than half of the stocks for Botswana, the BRVM, Egypt, Ghana, Kenya and Mauritius have significant first order serial correlation. For Morocco, Tunisia and Zimbabwe, the number of stocks with correlation coefficients significantly different from zero are less than half the respective sample sizes, but only marginally, and are a third of the sample size for Namibia.

Table 6.2: Number and proportion of stocks with significant first order serial correlation coefficients for each market

Stock Exchange	Sample size	Largest coefficient @ lag 1 (absolute)	Serial Correlation at lag 1						Overall market
			All stocks		Significant at the 5% level			Correlation	Proportions of rejections*
			positive	negative	positive	negative	total		
Botswana	12	0.337	6	6	3	4	7	NC	58.3%
BRVM	24	0.624	15	9	11	4	15	Positive	62.5%
Egypt	54	0.445	51	3	43	1	44	Positive	81.5%
Ghana	20	0.528	18	2	15	1	16	Positive	80.0%
Kenya	40	0.424	10	30	-	22	22	Negative	55.0%
Mauritius	9	0.429	4	5	4	2	6	NC	66.7%
Morocco	36	0.424	16	20	6	9	15	Negative	41.7%
Namibia	15	0.337	5	10	4	1	5	NC	33.3%
Tunisia	35	0.277	21	14	10	6	16	Positive	45.7%
Zimbabwe	39	0.161	25	14	13	5	18	Positive	46.2%

NC = Not clear

* This is equal to the number of stocks rejecting the random walk divided by the sample size (total number of stocks in the sample) as a percentage

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Not much emphasis is put on the serial correlation results. This is because the normality assumption was seriously violated, with the return series for almost all the stocks significantly deviating from normality at less than the 1% level of significance using the Kolmogorov-Smirnov test. The runs test, therefore, as a nonparametric measure, is more appealing due to its robustness.

6.4.3 Runs test results

Due to the non-normality of the returns series, a nonparametric measure for independence is necessary. In this regard, the runs test is used. This test is not affected by any extreme values in the return series (Dickinson and Muragu, 1994) and thus does not require constant variance of the data (Barnes, 1986). The hypothesis of independence is tested using the significance of the standardised Z-values at the 5% level of significance. This statistic compares the observed and expected number of runs. The observed number of runs is the sequences of price changes of the same sign. The total expected number of runs are computed as follows, (see Fama, 1965):

$$m = \frac{n(n+1) - \sum_{i=1}^{3} n_i^2}{n} \tag{6.4}$$

where n is the total number of price changes and n_i (i =1,2,3) are the numbers of price changes of each sign, that is, positive, negative and zero.

According to Fama (1965), for large n, the distribution of m is approximately normal and the Z-value is calculated as follows:

$$Z = \frac{r + \frac{1}{2} - m}{\sigma_m} \tag{6.5}$$

where r is the observed number of runs, the "$\frac{1}{2}$" is the discontinuity adjustment factor and σ_m is the standard error of m and is given by:

$$\sigma_m = \left(\frac{\sum_{i=1}^{3} n_i^2 \left[\sum_{i=1}^{3} n_i^2 + n(n+1) \right] - 2n \sum_{i=1}^{3} n_i^3 - n^3}{n^2(n-1)} \right)^{\frac{1}{2}} \tag{6.6}$$

where all the variables are as defined before.

A negative Z-value implies that the observed number of runs is less than the expected number of runs and thus positive dependency. The opposite is true for a positive Z-value.

The results show that relatively fewer stocks reject the random walk with the runs test than with the serial correlation test for all the markets except Ghana, Mauritius and Morocco. While the differences between the results of the two tests are only marginal for most of the markets, they are quite significant for Egypt and Kenya. For Egypt, 54 percent of the stocks reject the random walk with the runs test as compared to 82 percent with the serial correlation test, while for Kenya the proportions are 30 percent and 55 percent, respectively. For all the markets except Kenya, the runs test indicates positive dependency (see Table 6.3).

Table 6.3: Number and proportion of stocks with significant Z-values for the runs test

Stock Exchange	Sample size	Largest Z-values (absolute)	Runs Test Z-values						Overall market
			All stocks		Significance at the 5% level			Correlation tendency	Proportions of rejections*
			positive	negative	positive	negative	total		
Botswana	12	3.915	-	12	-	6	6	Positive	50.0%
BRVM	24	6.043	1	23	-	13	13	Positive	54.2%
Egypt	54	5.704	11	43	1	28	29	Positive	53.7%
Ghana	20	9.546	1	19	-	16	16	Positive	80.0%
Kenya	40	5.178	24	16	11	1	12	Negative	30.0%
Mauritius	9	6.644	-	9	-	9	9	Positive	100.0%
Morocco	36	4.550	10	26	-	17	17	Positive	47.2%
Namibia	15	2.194	6	9	-	1	1	NC	6.7%
Tunisia	35	7.937	9	26	1	14	15	Positive	42.9%
Zimbabwe	39	6.198	10	29	-	14	14	Positive	35.9%

NC = Not clear

* this is equal to the number of stocks rejecting the random walk divided by the sample size (total number of stocks in the sample) as a percentage

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Using the runs test, all the stocks for Namibia, except one, exhibit random walk behaviour at the 5% level of significance or better (see Table 6.3 and also Appendix

F3). For Kenya, Zimbabwe, Tunisia and Morocco, less than half the stocks in the respective samples reject the random walk. However, for Tunisia and Morocco, the proportions of stocks rejecting the random walk are only marginally less than half the sample sizes.

On the Mauritius stock exchange all the stocks in the sample reject the random walk hypothesis at the 1% level of significance using the runs test. More than half of the stocks for the BRVM (54 percent), Egypt (54 percent) and Ghana (80 percent), and exactly half the stocks for Botswana also reject the random walk using the runs test. While such proportions are only marginally greater half, they are significantly large for Mauritius and Ghana. The possibility of making abnormal returns cannot be ignored for these markets.

6.4.4 Higher order serial correlation

Bekaert and Harvey (2002) indicated that emerging market stock returns exhibit higher order serial correlation. In order to provide empirical evidence for this assertion in the current research, a hypothesis that the correlation coefficients of trade-to-trade returns at all lags are zero is tested against the alternative that not all correlation coefficients are zero. This hypothesis is tested using the Box-Ljung Q-statistic, which is given by:

$$Q = n(n+2)\sum_{\tau=1}^{k}\frac{\hat{\rho}_{\tau}^{2}}{n-\tau} \tag{6.7}$$

The Q-statistic is chi-square distributed with k degrees of freedom (χ_k^2). The Box-Ljung Q-statistic is statistically more powerful in small sample data than the Box-Pierce Q-statistic and is thus relevant in this study, given the small sample properties of the data used. The null hypothesis that all the ten correlation coefficients are zero is rejected if the Q-statistic for the 10 lags is significant at the 5% level of significance.

The numbers of correlation coefficients that are significantly different from zero across the 10 lags at the 5% level of significance are also presented (see Appendix F4). The results show that for all the markets, most of the stocks have at least one correlation coefficient that is significantly different from zero. The Box-Ljung Q-statistics for the hypothesis that the correlation coefficients for all lags (1 to 10) are equal to zero against the alternative that not all correlation coefficients are equal to zero are also presented. The results show that more than half of the stocks for each market, except Namibia and Zimbabwe, exhibit significant higher order serial correlation (see Table 6.4).

Table 6.4 shows that the numbers of significant coefficients decrease with increasing lags for both the ACF and PACF, but only gradually. Therefore, while stock returns in the immediate past provide information that play a significant role in determining future returns, the information becomes less and less useful the further away in the past one looks. However, for the African markets in this study, the importance of historical price information only dissipates gradually and is therefore not totally irrelevant in forecasting future returns.

Table 6.4: Number of significant higher order serial correlation coefficients and the proportions of significant Box-Ljung Q-statistics

Stock Exchange	ACF (for lags 2-10)									PACF (for lags 2-10)									Box-Ljung Q-stats
	2	3	4	5	6	7	8	9	10	2	3	4	5	6	7	8	9	10	Proportions of rejections*
Botswana	5	4	1	2	0	3	0	0	1	6	2	1	3	1	2	1	0	1	
BRVM	12	6	3	6	3	3	3	1	3	10	6	1	4	3	3	3	0	3	66.7%
Egypt	27	6	11	3	6	6	7	3	7	24	3	8	1	4	4	6	2	3	77.8%
Ghana	14	12	8	5	5	2	2	3	4	11	6	4	1	4	1	2	1	2	85.0%
Kenya	9	5	5	7	2	0	2	0	4	7	5	5	5	4	0	2	0	5	52.5%
Mauritius	2	1	3	1	3	1	0	3	0	3	2	3	0	3	0	0	3	0	55.6%
Morocco	6	8	5	4	3	0	7	3	2	7	7	6	3	2	0	5	3	2	50.0%
Namibia	1	1	2	1	1	2	0	0	0	3	1	2	2	1	2	0	0	0	20.0%
Tunisia	10	4	4	5	7	6	4	0	2	6	4	2	4	5	6	3	0	1	60.0%
Zimbabwe	5	6	6	4	2	1	3	3	4	7	4	6	5	4	1	2	2	3	43.6%
Total	91	53	48	38	32	24	28	16	27	84	40	38	28	31	19	24	11	20	

* This is equal to the number of stocks rejecting the random walk divided by the sample size (total number of stocks in the sample) as a percentage.
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

6.5 Discussion of results

The positive correlation observed on most of the markets is not surprising considering that daily data were used for an average period of 5 years. Positive serial correlation is usually considered to be a predictability phenomenon of the short-run, while negative correlation implies long run predictability. The positive serial correlation on African markets might be a result of institutions imitating each other, or spreading their trades over several days (1) to avoid suspicions of insider trading and (2) to lessen the impact of trades in large volumes on the market (Asal, 2000). Certain macroeconomic indicators such as inflation and interest rates are also likely to play an important role in predicting stock returns. Analysts attributed the rally on the Zimbabwe Stock Exchange in 2003 to the negative real interest rates, leaving equities as one of the few attractive investment avenues. Where a specific fiscal or monetary policy is expected to prevail, equity prices would tend to follow a specific trend unless interrupted by other factors or events. Because of the long-term nature of macroeconomic factors, positive serial correlation in returns might occur. However, this is just a possible explanation, which warrant further research.

The weak-form efficiency of the NSX can probably be explained by the market's positive correlation with the JSE due to the significant number of stocks that are dual-listed on both markets. Tyandela and Biekpe (2001) found the correlation of the two markets to be 90 percent and the highest for all the market correlations that were studied. Considering some of the recent studies, the JSE was found to be efficient in Magnusson and Wydick (2002); Smith and Jefferis (2002) and Smith, *et al.* (2002). If the JSE is weak-form efficient, then one can argue that the efficiency filters through to the NSX since almost the same stocks are traded on both markets. About two-thirds of the stocks, which make up the sample for Namibia, are dual-listed on the JSE. The efficiency of the NSX can thus be said to be a spillover from, or a reflection of, the weak-form efficiency of the JSE.

The NSX also happens to be the most thinly traded among the markets in the sample. When the trade-to-trade approach is used in the calculation of returns, fewer observations are obtained, especially for the thinly traded stocks. While the runs test is robust to the distribution of the data and extreme values, it depends more on the sample size. The fewer observations can give rise to lack of significance in the Z-values of the runs test. This is because the expected number of runs increases proportionately to the sample size, while the standard error increases proportionately to the square root of the sample size (Dickinson and Muragu, 1994; Fama, 1965). A visual inspection of the results (see the tables in Appendix F) does not clearly show any strong pattern of thinly traded stocks being less likely to reject the random walk than the most frequently traded stocks and vice versa. This is also supported by the Spearman's rank correlation test, the results of which are presented in Table 6.6 below. Except for Kenya and Zimbabwe, there are no significant correlations between rejection of the random walk and thin trading. Therefore, though the severe thin trading characteristic of the NSX might have contributed to the small Z-values observed, it is also likely that the market is indeed weak form efficient.

Table 6.5: The relationship between statistical significance and the stock's thin trading frequency

Spearman's rho	(a) Observed statistics[a]			(b) Count[b]		(c) Qualitative binary data[c]		
	(P)ACF Lag 1 coefficients	Runs test Z-values	Box-Ljung Q-statistics	Higher order PACF	Higher order ACF	(P)ACF Lag 1 coefficients	Runs test Z-values	Box-Ljung Q-statistics
Botswana	-0.371	0.294	-0.497	-0.700*	-0.530	-0.368	-0.169	-0.564
BRVM	0.217	-0.114	-0.292	-0.377	-0.519**	-0.299	0.284	-0.384
Egypt	0.274*	0.094	0.202	0.205	-0.091	-0.166	-0.062	-0.109
Ghana	0.457*	0.446*	-0.090	-0.188	-0.299	0.326	-0.250	-0.231
Kenya	0.461**	-0.684**	-0.675**	-0.495**	-0.457**	-0.657**	-0.548**	-0.512**
Mauritius	-0.517	0.483	0.017	-0.443	-0.068	-0.365	n/a	-0.173
Morocco	0.244	0.181	-0.284	-0.217	-0.267	-0.133	-0.212	-0.168
Namibia	0.071	-0.195	-0.152	-0.165	-0.080	-0.098	0.000	-0.193
Tunisia	0.251	0.081	-0.357*	-0.275	-0.178	-0.341*	-0.252	-0.263
Zimbabwe	-0.449**	0.662**	-0.509**	-0.420**	-0.537**	-0.274	-0.539**	-0.439**
All markets	0.009	0.112	-0.350**	-0.260**	-0.280**	-0.305**	-0.262**	-0.335**

** implies significance at the 1% level
* implies significance at the 5% level
The Spearman's rank correlation test was used to investigate if there is a correlation between the rejection of the random walk and the level of thin trading. The thin trading frequencies are correlated with the observed Z-values, first order serial correlation coefficients, or Box-Ljung Q-statistics. Binary data was also derived, taking the value of 1 when each of the aforementioned statistics is significant and 0 otherwise.
[a] the correlation between the actual observed statistics and the thin trading frequencies
[b] the correlation between the number of significant higher order coefficients and the thin trading frequencies
[c] The correlation between the thin trading frequencies and binary variables, taking the value of 1 when the statistic is significant and 0 otherwise
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

The efficiency of Kenyan and Zimbabwean stock exchanges shows how unjustifiable it is to draw conclusions on the informational efficiency of a market based on its operational and general characteristics. In fact, it renders unjust the perceptions that

African stock markets are not efficient because of their operational inefficiencies, as is currently the case. Although the Kenyan and Zimbabwean stock exchanges are relatively old, they both have restrictions on foreign participation, high withholding taxes and are both still using the open-outcry systems. The two markets limit the amount of shareholding in a single company by individual foreign investors to 10 percent, and by foreign investors collectively to 40 percent. Kenya has withholding taxes of 10 percent (5 percent for residents) on dividends and 15 percent on interest earned on bonds, while capital gains taxes have been suspended. Zimbabwe, on the other hand, has withholding taxes to non-residents of 15 percent on dividends, and 10 percent on both interest income and capital gains, and a stamp duty of 45 cents per Z$100. Commission fees range from 1.1 percent to 2 percent in Kenya and 1 percent to 2 percent in Zimbabwe. While most of the markets were using electronic trading for the period investigated, Zimbabwe and Kenya were, and are still, using the call-over/open-outcry systems.

While free entry and exit of investors in a market and a shift of the trading system from a call-over/open-outcry to electronic trading are believed to enhance price stability, increase transparency, liquidity and efficiency, this notion is not supported by our results. Zimbabwe and Kenya are relatively efficient despite the restrictions on foreign participation and the fact that they are not using electronic trading. This lack of association between informational and operational efficiency is also supported by evidence in Appiah-Kusi and Menyah (2003). Using rank correlation analysis, they found that the weak-form inefficiency of six African markets in their study was not associated with trading volume, number of firms, market capitalisation, transfer taxes or trading commissions.

The deviation from the random walk portrayed by the sampled stocks listed on the stock exchange of Mauritius also supports the observation that informational and operational efficiencies are not associated. The market uses an automated trading system, it has no withholding taxes and commissions are very low. The market is also open to foreign investors except for the 15 percent commission charged on foreign investments in sugar companies. The rejection of random walk on this market may be due to investors not reacting quickly to new information and thus a slow adjustment of prices. This slow reaction could be due to a possible wait-and-see attitude by investors on this market. Market participants might also perceive transaction costs to be high such that they would wipe out any potential gains.

The rejection of the random walk by some Ghanaian stocks could be due to limited trading time on this market. The GSE trades only three times a week, on Mondays, Wednesdays and Fridays. This could result in price adjustment delays and thus partly explain why stock prices on this market deviate from the random walk. If new information arrives on a Tuesday, which is a nontrading day on the Ghana Stock Exchange, investors would be in a position to reasonably predict the price movements for Wednesday when the stock market opens for trade.

While correlation among major markets appears to have risen over the last 30 years, correlations of major markets with emerging markets remain relatively low (Hassan, *et al.,* 2003). The lack of correlation between African markets and developed markets, though attractive for portfolio diversification, also imply that the African markets tend to lag the development of major markets, in term of, for example, liquidity and efficiency. The JSE and, indirectly, the NSX, are relatively more correlated with developed markets than the other African markets, which might explain why they are relatively more efficient. Smith and Jefferis (2002) found the correlation of the JSE with the S&P500 and FTSE100 to be 0.53 and 0.42, respectively and relatively small for the other African markets.

Not only do African markets lack integration with developed markets, but most of them also lack integration with each other. This could be part of the reason why they have remained small and illiquid. The number of listed stocks has remained relatively constant on most African markets, not necessarily because there are no new listings but because these tend to cancel out with delistings. Most of the delistings probably occur because the stocks are not frequently traded such that when negative news arrives in the market, investors would tend to dump all their shareholdings of the company reporting the bad news when they get the chance. The stocks listed are also comparatively small except for a few multinational corporations, which explain the small size in terms of market capitalisation. The Namibian market, which was found to be efficient, is the largest in the sample in terms of market capitalisation due to the dual-listing of its stocks on the JSE. Increasing the number of tradable instruments might also help lower costs, reduce risk exposures, increase the number of transactions and liquidity and thus deepen the financial markets. Another measure of dealing with the small sizes and illiquidity of African stock markets might be the establishment of regional stock exchanges, which can enhance the ability of national capital markets to raise capital for their companies.

Besides the restrictions on foreign participation, some of the regulatory weaknesses include restrictions on short selling, inadequate rules on information disclosures, nonexistent insider trading laws and inadequate investor protection rules. The lack of regulations on insider trading negatively impacts on the confidence and perceived risk of investing on the markets. A proper and effective regulatory framework is, however, fundamental for the efficient operation of a stock market. The US capital market is considered the most regulated, but it is also the largest and most efficient market in the world. Institutional reforms that include rejuvenating the regulatory framework could, therefore, enhance efficiency, increase liquidity and reduce volatility, thus promoting stock market development. Introducing a market regulator is often seen as a signal of a strengthening regulatory framework. A key regulator in capital markets is an agency, whose job is to promote the operation of virtuous, competitive and efficient markets.

Fama (1965: 38) highlighted the importance of many sophisticated traders in a market, who can recognise situations where the price of a stock runs well above or below its intrinsic value, and who through their actions would cause such price bubbles to burst before they get underway. Lack of sophisticated, well-informed traders on African markets may partly cause bubbles that stay for a long time before they are discovered. There is also lack of research to explore informational inefficiencies that might be existent so that any inefficiency discovered will be arbitraged into non-existence. Market participants may also have unrealistic risk-return expectations for their investments. African markets, therefore, would gain significantly by improving market quality. Removing restrictions on foreign participations, for example, would increase the number of sophisticated traders and thus enhance the value of traded assets. Well-structured, virtuous and transparent markets with many buyers, sellers and an effective regulatory system are likely to be efficient. Although operational efficiency does not necessarily mean informational efficiency, the two are inseparable for a market's development.

The results are partly consistent with findings in some prior studies. Smith, *et al.* (2002) found Egypt, Morocco, and Mauritius to be inconsistent with weak-form efficiency. In this study, the same markets indicate a significant number of stocks rejecting the random walk. Magnusson and Wydick (2002) found Ghana not to conform to random walk 3 and Botswana to random walk 2. Appiah-Kusi and Menyah (2003) considered Botswana, Ghana and the Ivory Coast to be inconsistent and Kenya and Zimbabwe to be consistent with weak-form efficiency. Appiah-Kusi and Menyah (2003), however, concluded on the contrary that Egypt, Morocco and Mauritius are weak-form efficient and South Africa is inefficient. Kiweu (1991) and Dickinson and Muragu (1994) concluded that Kenya is weak-form efficient. Chiwira (2001) arrived at similar conclusions for Zimbabwe, while Bundoo (2000) concluded that the Stock Exchange of Mauritius is not consistent with weak-form efficiency. Asal (2000) concluded that the Egyptian Stock Exchange was not weak-form efficient for the period 1992 to 1996, but was moving towards efficiency in 1997. Though, prior studies for Namibia have not been found, Magnusson and Wydick (2002); Smith and Jefferis (2002) and Smith, *et al.* (2002), among others, found the JSE to be weak-form efficient. This partly supports the explanation of a spill-over effect from the JSE to the NSX.

The correlation coefficients and Z-values are, however, small in magnitude for some stocks, but relatively large for others in comparison to those obtained in, for example, Dickinson and Muragu (1994), and Fama (1965). The largest serial correlation coefficients exceed 0.5 for the BRVM (0.624) and Ghana (0.528) and the Z-values, which are significant at the 1% level of significance, exceed 5.0 for a number of stocks across markets, reaching to as high as 9.546 for Ghana (see Appendix F3). In Fama (1965), the largest first order serial correlation coefficient in absolute terms was only 0.123 and the largest standardised value for the runs test, also in absolute terms, was 4.23. Dickinson and Muragu (1994) also found very small values in their study of the Nairobi Stock Exchange, with the largest serial correlation coefficients and Z-values in absolute terms of 0.127 and 2.987, respectively. While Fama (1965) and Dickinson and Muragu (1994) hinted that such coefficients may not be attractive to investors, we cannot entirely dismiss them as unimportant is this study. There is a slight chance in this case that one can forecast and obtain abnormal returns when using historical price patterns or trade-to-trade returns on some, though not all, of the African markets.

6.6 Conclusion

This chapter investigated the weak-form efficiency of ten African stock markets using the serial correlation and runs test. Returns were calculated on a trade-to-trade basis, an approach that has been supported for thinly traded markets. The returns obtained from this approach are of varying intervals and tend to reflect the length of the interval. This justifies adjusting each trade-to-trade return by weighting by the number of days between trades.

Serious thin trading was observed on all markets, and more so for Namibia and Botswana, the two markets with significant dual-listed stocks on the JSE. In all the markets studied (except Namibia), a significant number of stocks rejected the random walk. Considering that all the stocks in the Namibian sample have thin trading frequencies of more than 50 percent, the question arising was to what extent this could have contributed to the results. The Spearman rank test led to the conclusion that despite its thin trading nature, the weak-form efficiency of the NSX is attributed to its correlation with the JSE. The Kenyan and Zimbabwean stock exchanges were also found to be weak form efficient, since a significant number of stocks conformed to the random walk.

All the stocks in the Mauritius sample rejected the random walk at the 1% level of significance using the runs test. This led to the conclusion that there are chances of making abnormal gains using historical price information on the Mauritius market. The same conclusion was made for Ghana. On the BRVM, Egypt and Botswana stock exchanges, chances of making abnormal gains could also not be dismissed. The results also indicate some higher order serial correlation, supporting the literature that emerging markets have relatively higher order serial correlation than developed markets. This could be due to price adjustment delays as a result of thin trading.

Since rejection of the random walk does not necessary mean weak-form inefficiency, but only implies serial correlation in stock returns, it is vital to investigate whether such serial correlation can be exploited for abnormal returns, net of transaction costs. If abnormal gains can be obtained from trading strategies devised to exploit this observed serial correlation, then the respective market is weak form inefficient. Since such further tests are rather involved, they are left for future research.

7 IMPLICATIONS OF THIN TRADING FOR MARKET EFFICIENCY TESTING

7.1 Introduction

The problem that thin trading poses in financial markets research has been widely acknowledged (see for example, Atchison, *et al.*, 1987; Bowie, 1994; Cohen, *et al.*, 1983; Dimson, 1979; Lo and MacKinlay, 1990a, 1990b; Miller, *et al.*, 1994). Lo and MacKinlay, 1990a p181) argued 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. Fisher (1966), the first to identify the bias of thin trading in index returns, pointed out that recorded prices of securities are not necessarily equal to their underlying theoretical values such that the indices constructed from these share prices are only an average of the temporally ordered underlying values of the shares. This is because if a share does not trade, the price recorded is the transaction price when the share was last traded.

Although it is generally perceived that African stock markets are thinly traded, to the best of our knowledge, no empirical investigation has been done on this except in the case of the Johannesburg Securities Exchange (JSE) (e.g., Bowie, 1994). However, such evidence is critical for the understanding of the dynamics of African stock markets by academics and market practitioners. For academics, the evidence will most certainly impact on model selection in tests performed on these markets. For market practitioners, such evidence will impact on investment decisions.

This study takes the academic's perspective on the implications of thin trading on market efficiency testing. The method is to compare results obtained using different return measurement methods. Any differences observed are assumed to partly explain the contradictions in the evidence on market efficiency for some thinly traded markets. While other factors certainly contribute to the contradictions, inconsistencies in addressing the thin trading problem could be one major factor. The study also examines how much of the first order serial correlation in observed individual stock returns is induced by thin trading. This is done using the nontrading[1] model developed by Lo and MacKinlay (1990a). The study does not, however, extend the investigation to portfolio returns but leaves it for future research.

7.2 Thin trading: literature review

The literature on thin trading has focussed mainly on the bias it poses on beta or systematic risk estimation. Dimson (1979) explained that the explanatory power of the market model and the mean value of beta, estimated from value-weighted indices, tend to rise as the differencing interval increases. He pointed out that since the mean beta of all shares is unity, simple regression of the market model generates upward biased estimates of the risk of frequently traded shares, and downward biased estimates of the risk of infrequently traded shares. The movement of beta towards unity as the differencing interval is increased, according to Dimson (1979), is an indication that much of the variation in betas is due to the nontrading bias.

In efficiency testing, thin trading induces serial correlation in the return series. For individual stocks, thin trading tends to increase the number of zeros in a return series. The zero returns resulting from the stock not having traded have been termed 'false' zero returns by Strebel (1978). Some researchers (e.g. Kiweu, 1991), however, disregard all zero returns even if the stock is traded. Although this method is seriously flawed, such researchers base their arguments on the notion that such returns result from trade not based on information and therefore no adjustment to prices. Any news that does not contribute to price changes is considered to have no information content. If information is of any value to an investor, the expectation is that it will impact on the value of prices.

[1] Throughout the chapter, thin trading and nontrading will be used interchangeably. This is because thin trading in this chapter refers to the infrequency with which a stock trades. In the use of daily data, which is the highest frequency data available on most markets, thin trading would be measured by the number of days a stock does not trade as a proportion of the number of trading days for the period under investigation.

Cohen, *et al.* (1978), however, highlighted that the closing transaction prices unlike the closing quotes need not reflect all current information. They described two shifts in the market demand to hold a security, which they termed 'aggregate' and 'idiosyncratic' shifts. They described an aggregate shift as one that occurs in response to information that is generally available to all investors. The shift produces a new quoted price, but not necessarily a new transaction price for the security. An idiosyncratic shift, on the other hand, is one that occurs when an individual investor with excess funds or liquidity needs, changes his risk-return preferences, or reassesses his evaluation of a security's value. A large number of such shifts trigger transactions and will imply a new recorded transaction price. Cohen, *et al.* (1978) seem to suggest that while not all information will result in transactions, not all transactions are based on new information.

Lo and MacKinlay (1990a) illustrated that nontrading does not affect the mean value of observed returns but it increases the variance if the security has a nonzero expected mean. Atchison, *et al.* (1987) argued that individual security returns based on observed transaction prices should be slightly negatively first order autocorrelated. This negative serial correlation in individual security returns at all leads and lags is induced by nonzero expected returns and it decays geometrically (Lo and MacKinlay, 1990a)). According to Lo and MacKinlay (1990a) the autocorrelation becomes zero if the security's mean return is zero. They indicated, however, that this implication of nonsynchronous trading does not extend to the observed returns of portfolios.

Thin trading induces positive serial correlation in index returns and the estimated variances of index returns are biased downwards (Dimson, 1979). In an investigation of the extent to which nonsynchronous trading explain the observed autocorrelations, Atchison, *et al.* (1987) found the level of autocorrelation (predicted from their nonsynchronous trading model) to be well below the observed autocorrelation. This led them to conclude that the observed high autocorrelation values are not well explained by the nonsynchronous trading model. Part of the observed autocorrelation can be attributed to other factors or inefficiencies in the pricing process.

Thin trading presents an even more serious problem when estimating covariances and cross correlations between return series of two shares (Bowie, 1994). This is because there are few cases when both shares trade at the same time. Infrequently traded shares tend to lag the frequently traded shares and vice versa. If news affecting the aggregate market arrives towards the close of the market, it is most likely that the frequently traded share will reflect the information immediately while the infrequently traded share responds with a lag (Lo and MacKinlay, 1990a).

A number of methods for correcting the bias caused by thin trading have been proposed and among them is the trade-to-trade (TOT) approach. In systematic risk estimation, returns are calculated on a trade-to-trade basis and regressed on market movements calculated over precisely the same TOT time intervals (Dimson, 1979). The TOT approach, therefore, eliminates the problem of thin trading from the outset. It, however, requires knowledge of each share's exact transaction dates. In systematic risk estimation, it also require a market index with negligible nontrading. The TOT approach integrates the variability in the interval length, in that the intervals over which returns are measured are allowed to vary in length depending on when the share was last traded. Bowie (1994) observed that the extent of non-normality in the return series depends on the length of the interval over which returns are measured. He found that the variances and means of return series tend to increase proportionally to the length of the interval over which they are measured. He, therefore, stated that "it appears reasonable that the average weekly return be approximately five times the average daily return and that the variance be similarly increased five-fold in going from daily to weekly returns" (Bowie, 1994: 4-8).

Ekechi (1989) also found that the stocks on the Nigerian Stock Exchange (NSE), on average, exhibit more extreme leptokurtosis than in a normal distribution. He suggested that this is because the number of trading days between transactions varies for these less frequently traded shares, which may result in "polluted" data through the mixing of different distributions. He went on to suggest that the most probable explanation is the fact that one is sampling from populations of price changes which are not the same, that is, the number of trading days between transactions differ.

Most empirical research on efficiency, particularly on emerging stock markets, remains inconclusive (e.g. Dezelan, 1999; Strebel, 1977, 1978; Bundoo, 2000; Osei, 2002). It is believed that the serial correlation, (especially higher order serial correlation evident on these markets) is symptomatic of infrequent trading and thus the slow adjustment of prices to information (e.g., Bekaert and Harvey, 2002). Ekechi (1989), using a sample of the 20 most actively traded stocks (in terms of sales volume) on the NSE found that none of the stocks were traded on every single day for the period covered. The most active stock in the sample traded only for 509 days out of the 1512 trading days for the period. He examined whether prices of infrequently traded shares deviate more from the random walk hypothesis than the prices of frequently traded shares using only the closing transaction prices when there was a trade (the TOT). He concluded that the NSE stocks appear to deviate from the random walk hypothesis with the prices of infrequently traded shares deviating more from the random walk than the prices of more actively traded shares.

While thin trading is argued to induce much more serious autocorrelation in portfolio or index returns than in individual stock returns, only two studies on African stock markets that did adjust for thin trading in index returns in the testing of the random walk hypothesis have been accessed by the author. These are Asal (2000) and Appiah-Kusi and Menyah (2003). Both studies used the adjustment method for thin trading in index returns proposed by Miller, *et al.* (1994).

7.3 Data and methodology

Daily stock price data for 10 African stock markets is used to calculate returns. Daily volume traded data is also used as additional information to determine each stock's exact trading time, as required by the trade-to-trade (TOT) approach. The data range from 4 January 1999 to 31 December 2002 for the West African Regional Exchange - *Bourse Regionale des Valeurs Mobilieres* (BRVM), 1 June 1998 to 31 December 2002 for Mauritius, 23 March 1998 to 31 May 2002 for Botswana, 2 January 1998 to 31 December 2002 for Ghana and Tunisia, and from 2 January 1997 to 31 May 2002 for Egypt, Kenya, Morocco, Namibia and Zimbabwe.

Continuously compounded returns are calculated as follows:

Normally;

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{7.1}$$

Using the trade-to-trade (TOT) approach;

$$R_t^{(K_t)} = \ln(P_t) - \ln(P_{t-K_t}) \qquad (7.2)$$

Using the TOT approach adjusted for variability in the interval lengths (ATT);

$$\widetilde{R}_t = \frac{1}{K_t}\left[\ln(P_t) - \ln(P_{t-K_t})\right] \qquad (7.3)$$

R_t is the return for the period $t-1$ to t; P_t is the closing share price recorded at time t; P_{t-1} is the closing share price recorded at time $t-1$; $R_t^{(K_t)}$ is the TOT return in period *t*, given that there was trade; P_{t-K_t} is the price of a stock K_t periods in the past; K_t is the length of time between the trade in period *t* and the previous successively traded day; $\widetilde{R}_t$ is the approximate one-day return after adjusting for variability in the interval length; and " ln " is the natural logarithm operator.

The TOT approach uses closing prices only for those days when trade actually took place. It has been considered the best approach for calculating returns in a thinly traded market (see Bowie, 1994; Dimson, 1979). Whether or not a stock was traded on a given day, in this study, is determined using volume traded data, with zero-volume implying there was no trade, and a positive volume implying there was trade for the stock in question. The TOT approach, however, integrates the variability in the interval length, in that the intervals over which returns are measured are allowed to vary in length depending on when the share was last traded. The ATT approach, corrects for this variability in the interval lengths by weighting each TOT return by the number of days between trades (see Mlambo, *et al.*, 2003).

Almost all the return series using the different return calculation methods are stationary. Stationarity is tested using the Augmented-Dickey-Fuller test with and without a time trend (see Appendix G).

7.4 Empirical evidence

7.4.1 Thin trading on African stock markets

Table 7.1 describes the thin trading characteristics of the ten African stock markets. For each market, the stocks are divided into quartiles based on the thin trading frequencies, with the first quartile having the most frequently traded stocks and the fourth quartile having the most infrequently traded stocks. It is evident from the table that there is considerable thin trading on almost all the markets, with the mean duration of nontrading reaching to as high as 36 days for the most thinly traded stocks in Morocco. Egypt seems to show very little thin trading but this is only because the sample was selected from only the 70 most actively traded stocks, which are the only stocks where data could be obtained. More than 600 stocks, making up the rest of the market, are not covered in most market reports, as they are inactive.

The evidence in Table 7.1 shows that in quartile 1, the duration of nontrading is zero days at least 90 percent of the time for Egypt, Kenya, Morocco and Tunisia. For all the markets, quartile 1 exhibits the greatest proportion of durations of nontrading of zero-days' length and quartile 4 the lowest. The duration of nontrading does not exceed 5 days for quartile 1 for Kenya, Egypt, Morocco and Tunisia. For Namibia[2], however, all the quartiles have nontrading durations exceeding 40 days while for the other markets, it is only in quartile 4, consisting of the most thinly traded stocks, where the duration of nontrading exceeds 40 days. This means that for Namibia, and quartile 4 of the other markets, a stock may not trade for more than 2 months in a row.

7.4.2 Comparison of return measurement methods in random walk testing

The return series from the three return measurement methodologies are tested for the random walk using the serial correlation and runs tests. It is important to note that the runs test is robust to the interval effect since it only relies on the signs and the length of their uninterrupted sequences. Therefore, the TOT and ATT approaches would give the same result using the runs test, but not necessarily with the serial correlation test.

[2] Two-thirds of the stocks in the Namibian sample are dual-listed on the JSE. Therefore, trading in these stocks probably takes place more on the JSE than on the Namibian Stock Exchange

Table 7.1: Infrequency of trading on selected African stock markets

Stock Exchange	Quartile*	Number of Stocks	Nontrading frequency (%) Range		Mean duration of nontrading (days) Range		Distribution of duration of nontrading (days)								Average number of observations per stock
			from	to	from	to	0 (%)	1 to 2 (%)	3 to 5 (%)	6 to 10 (%)	11 to 20 (%)	21 to 40 (%)	Over 40 (%)	Total (%)	
Botswana	1	3	34.5	50.0	0.53	1.00	61.6	29.9	7.1	1.2	0.2	0.0	0.0	100.0	600
	2	3	50.6	68.4	1.01	2.17	47.5	31.6	14.8	5.0	1.1	0.0	0.0	100.0	425
	3	3	77.6	85.2	3.45	5.80	19.2	28.2	21.9	17.4	11.0	1.9	0.3	100.0	183
	4	3	89.8	93.6	8.71	13.85	14.0	18.4	13.3	20.4	20.8	9.1	4.0	100.0	91
BRVM	1	6	3.2	49.6	0.03	0.97	72.0	21.6	4.1	1.5	0.6	0.0	0.0	100.0	442
	2	6	54.7	63.5	1.21	1.67	57.3	27.2	8.7	4.2	1.8	0.7	0.1	100.0	272
	3	6	67.2	82.8	2.06	4.74	40.4	30.6	14.2	7.4	3.9	2.7	0.7	100.0	163
	4	6	84.4	94.9	4.65	17.42	30.5	28.0	13.4	9.7	7.6	4.9	6.0	100.0	77
Egypt	1	14	4.8	6.8	0.05	0.07	95.7	3.9	0.4	0.0	0.0	0.0	0.0	100.0	1263
	2	13	7.2	17.7	0.08	0.21	92.2	7.0	0.7	0.1	0.0	0.0	0.0	100.0	1192
	3	13	18.6	51.1	0.23	1.02	76.8	17.0	4.1	1.3	0.5	0.1	0.1	100.0	848
	4	14	52.5	74.2	1.10	2.87	59.5	25.3	8.7	3.7	1.7	0.7	0.4	100.0	515
Ghana	1	5	9.8	38.0	0.10	0.56	80.0	17.5	2.1	0.3	0.1	0.0	0.0	100.0	578
	2	5	43.0	69.8	0.68	1.90	56.9	30.2	9.4	2.5	1.0	0.1	0.0	100.0	376
	3	5	70.6	76.6	1.90	2.47	41.9	30.6	16.7	7.4	3.0	0.4	0.0	100.0	238
	4	5	80.6	87.2	2.78	3.99	41.7	28.7	15.1	7.8	4.0	1.5	1.2	100.0	174
Kenya	1	10	2.0	15.8	0.02	0.19	92.6	6.9	0.5	0.0	0.0	0.0	0.0	100.0	1246
	2	10	17.5	51.5	0.21	1.04	68.8	24.2	5.2	1.5	0.2	0.0	0.0	100.0	848
	3	10	54.8	74.5	1.21	2.89	45.3	30.6	14.4	6.5	2.7	0.4	0.1	100.0	479
	4	10	75.8	97.1	3.13	31.32	28.1	24.0	18.3	11.8	9.4	4.9	3.5	100.0	203
Mauritius	1	2	13.6	18.2	0.16	0.22	84.9	14.4	0.7	0.1	0.0	0.0	0.0	100.0	1006
	2	2	19.1	21.4	0.24	0.27	82.2	16.1	1.6	0.1	0.0	0.0	0.0	100.0	954
	3	2	29.3	32.3	0.42	0.48	71.2	25.3	3.3	0.2	0.0	0.0	0.0	100.0	827
	4	3	41.7	51.9	0.71	1.07	59.2	29.5	9.0	1.8	0.5	0.1	0.0	100.0	623
Morocco	1	9	0.9	13.1	0.01	0.15	95.1	4.8	0.2	0.0	0.0	0.0	0.0	100.0	1276
	2	9	14.4	45.9	0.17	0.85	77.4	18.7	3.3	0.5	0.1	0.0	0.0	100.0	982
	3	9	51.3	72.3	0.52	2.58	53.1	30.0	10.9	4.3	1.2	0.3	0.2	100.0	539
	4	9	73.8	97.5	2.81	35.91	24.8	23.1	15.1	12.5	8.3	8.0	8.2	100.0	164
Namibia	1	4	62.4	75.5	1.66	3.07	43.9	27.1	15.6	7.8	4.4	0.8	0.3	100.0	396
	2	4	82.7	86.7	4.77	6.20	33.1	23.9	16.6	10.7	8.6	5.3	1.8	100.0	197
	3	3	87.8	90.5	6.74	8.58	27.2	23.5	15.9	12.6	10.5	5.6	4.8	100.0	143
	4	4	93.3	97.6	10.03	17.78	21.5	17.1	16.9	13.6	11.9	8.5	10.5	100.0	65
Tunisia	1	9	1.8	8.8	0.02	0.10	95.6	4.2	0.2	0.0	0.0	0.0	0.0	100.0	1183
	2	9	11.1	31.6	0.12	0.45	83.8	14.0	1.9	0.3	0.0	0.0	0.0	100.0	996
	3	8	35.3	65.8	0.54	1.93	60.9	25.3	8.4	3.8	1.3	0.3	0.0	100.0	603
	4	9	72.7	91.4	2.64	10.35	32.6	25.1	17.9	10.0	8.3	4.2	1.9	100.0	225
Zimbabwe	1	10	4.4	31.6	0.05	0.46	79.3	18.3	2.3	0.1	0.0	0.0	0.0	100.0	1045
	2	10	34.5	48.9	0.53	0.96	62.2	29.2	7.2	1.3	0.1	0.0	0.0	100.0	780
	3	9	49.2	66.3	0.97	1.96	47.0	33.8	13.6	4.6	1.0	0.1	0.0	100.0	562
	4	10	69.8	93.9	2.31	15.43	26.3	27.3	19.4	14.3	7.6	3.7	1.5	100.0	264

*Quartile 1 represents the most frequently traded stocks and quartile 4 the stocks with severe thin trading
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

The serial correlation and runs tests results for the random walk hypothesis are presented in Table 7.2. The table seems to indicate that, except for the runs test results for Botswana, there are no major differences in the random walk test results from the different methods of measuring returns. However, while one stock could be found to reject the random walk with one approach, the same stock might not do so when returns are measured using a different approach.

Table 7.2: Serial correlation and runs test results for the different methods of measuring returns

Country/ Stock Exchange	# Sample stocks	Average number of observations per stock		Number of stocks with significant Runs Test Z-Values*		Number of stocks with significant first order serial correlation coefficients*			Number of stocks with at least one significant higher order serial correlation coefficient*@			Total number of significant higher order serial correlation coefficients*@		
		ENT	TOT/ ATT	ENT	TOT/ ATT	ENT	TOT	ATT	ENT	TOT	ATT	ENT	TOT	ATT
Botswana	12	1034	325	1	6	6	6	7	9	10	10	24	19	17
BRVM	24	686	239	9	13	11	11	15	18	15	18	40	21	33
Egypt	54	1341	952	42	29	47	40	44	35	34	38	65	53	55
Ghana	20	753	342	13	16	12	15	16	18	13	16	54	27	32
Kenya	40	1365	694	15	12	22	24	22	24	24	22	41	37	33
Mauritius	9	1196	827	8	9	7	6	6	7	7	8	19	9	14
Morocco	36	1348	740	14	17	12	13	15	29	21	24	49	34	35
Namibia	15	1340	204	6	1	2	6	5	8	10	9	10	13	11
Tunisia	35	1249	756	20	15	14	14	16	23	23	21	44	35	31
Zimbabwe	39	1352	665	10	14	13	13	18	27	23	23	55	40	34

ENT= 'entire' or normally calculated return series; TOT=trade-to-trade return series; ATT=adjusted trade-to-trade return series

* Using the 5% level of significance

@ Only 10 lags were used

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

7.4.2.1 Kendall's W test and the Wilcoxon signed ranks test

The differences in the random walk test results obtained from the different return measurement methods are not apparent in Table 7.2. In order to statistically investigate the differences, Kendall's W test for several-related samples and the Wilcoxon Signed Ranks test for two-related samples are used on data consisting of the actual observed first order serial correlation coefficients, runs test Z-values and number of significant higher order serial correlation coefficients. The hypothesis tested is that there are differences in the random walk test results for the different approaches of measuring returns.

Kendall's W test gives two statistics, the Chi-square Q statistic and Kendall's W coefficient of concordance. The latter statistic measures agreement in cases in rating each variable, where the cases are the results for individual stocks and the variables are the random walk test results for the ENT, TOT and ATT series. This coefficient ranges from '0' for no agreement to '1' for total agreement.

Table 7.3: Comparison of serial correlation test results for the different approaches of measuring returns

Country/ Stock Exchange	(a)					(b)
	Kendall's W[a]	Chi-Square Q	Wilcoxon Test			Wilcoxon Test
			TOT - ENT	ATT - ENT	ATT - TOT	TOT - ENT
Botswana	0.194	4.667	-1.961*	-0.786	-1.334	-2.824**
BRVM	0.158	7.583*	-3.115**	-2.800**	-0.057	-2.286*
Egypt	0.182	19.626**	-3.742**	-4.616**	-0.870	-6.229**
Ghana	0.273	10.900**	-2.334*	-2.875**	-0.710	-2.315*
Kenya	0.093	7.400*	-2.635**	-2.339*	-0.370	-3.414**
Mauritius	0.383	6.889*	-2.310*	-1.718	-0.178	-1.244
Morocco	0.021	1.535	-0.102	-1.089	-1.794	-0.330
Namibia	0.284	8.533*	-2.330*	-1.221	-1.420	-1.477
Tunisia	0.145	10.115**	-2.039*	-1.343	-3.283**	-0.524
Zimbabwe	0.229	17.897**	-2.952**	-0.768	-4.320**	-4.005**

** implies significance at the 1% level * implies significance at the 5% level
Significance implies that there are differences in the random walk test results.
ENT= 'entire' or normally calculated return series; TOT=trade-to-trade return series; ATT=adjusted trade-to-trade return series
[a] Kendall's W measures the agreement between cases in rating the variables. Values close to zero imply little agreement and values close to one imply high agreement
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

In panel (a) of Table 7.3, all the Kendall's W coefficients of concordance are relatively small (less than 0.5) implying that there is little agreement in the serial correlation test results for individual stocks. The Chi-square test also shows that there are significant differences in the first order serial correlation from the three return measurement methodologies. When variables are paired, the Wilcoxon test shows significant differences particularly between ENT and the other variables for most of the markets. There are significant differences (at the 5% level) between TOT and ATT only for Tunisia and Zimbabwe. For the runs test, the Wilcoxon Signed Rank test for paired variables shows significant differences, at the 5% level, between the pairs of variables as defined for the markets, except for Mauritius, Morocco, Namibia and Tunisia (see panel (b) of Table 7.3). There is only one pair of variables tested for the runs test results because the TOT and ATT results are identical.

For higher order serial correlation, the Chi-square Q statistics (see Table 7.4 panel (b)) show significant differences at the 5% level among all variables only for the BRVM and Ghana. The Wilcoxon Signed Ranks test for paired variables (Table 7.4 panel (c)) also shows that there are significant differences at the 5% level between at least one pair of variables for the BRVM, Ghana, Morocco and Zimbabwe.

Table 7.4: Comparison of number of higher order serial correlation coefficients for the different approaches of calculating returns

Stock Exchange	(a)	(b)	(c)		
	Kendall's W[a]	Chi-Square Q	TOT - ENT	ATT - ENT	ATT - TOT
Botswana	0.098	2.341	-1.184	-1.469	-0.491
BRVM	0.181	8.687*	-2.343*	-1.106	-2.029*
Egypt	0.006	0.677	-1.240	-1.115	-0.173
Ghana	0.230	9.186**	-2.627**	-2.954**	-1.129
Kenya	0.022	1.768	-0.579	-1.118	-0.402
Mauritius	0.289	5.200	-1.802	-0.756	-1.890
Morocco	0.079	5.663	-1.974*	-2.029*	-0.369
Namibia	0.025	0.743	-0.749	-0.264	-0.302
Tunisia	0.026	1.824	-1.260	-1.340	-0.702
Zimbabwe	0.056	4.373	-1.819	-2.420*	-1.096

** implies significance at the 1% level * implies significance at the 5% level

Significance implies that there are differences in the number of higher order serial correlations from the different return measurement methodologies.

ENT= 'entire' or normally calculated return series; TOT=trade-to-trade return series; ATT=adjusted trade-to-trade return series

[a] Kendall's W measures the agreement between cases in rating the variables. Values close to zero imply little agreement and values close to one imply high agreement

Source: Chipo Mlambo (2003), University of Stellenbosch Business School

The findings so far makes it interesting to measure the amount of serial correlation in individual stock returns that is induced by thin trading. This is done in the next subsection.

7.4.3 Thin trading-induced serial correlation

Much of the literature on the effect of thin trading on the random walk hypothesis has focussed on the autocorrelation it induces on portfolio returns (see for example, Atchison *et al.* (1987). This is because individual stock returns have been proven on other markets to have very little autocorrelation[3]. Atchison *et al.* (1987) argued that while observed daily returns on individual stocks exhibit, on average, only slightly positive first order autocorrelations, as observed in Fama (1965), market indices exhibit pronounced positive values. The positive first order autocorrelation in market index returns will be more severe when more weight is given to thinly traded securities, such as in an equal-weighted market index (Atchison *et al.*, 1987).

In this section, we investigate how much of the autocorrelation observed in individual stock returns (equation 7.1) is due to infrequent trading. The empirical evidence on the nontrading-induced autocorrelation on African stock markets would help to explain why correcting for the thin trading is necessary in empirical research on these markets.

[3] The literature that makes this argument refers mostly to the results of Fama (1965) for the Dow Jones Industrial Average (DJIA) 30 stocks

The investigation is done using the following stochastic nontrading model developed by Lo and MacKinlay (1990b):

$$\mathrm{corr}[R_{it}^{o}, R_{it+n}^{o}] = \frac{-\mu_i^2 p_i^n}{\sigma_i^2 + \dfrac{2p_i}{1-p_i}\mu_i^2}, \qquad n > 0, \tag{7.4}$$

where $\sigma_i^2 \equiv \mathrm{var}[R_{it}]$

R_{it}^{o} is the observed continuously compounded return for stock i at time t; R_{it+n}^{o} is the observed return for stock i at time $t+n$; μ_i is the mean return for stock i; p_i is the probability that stock i does not trade; R_{it} is the 'virtual'[4] return for stock i at time t; σ_i^2 is the variance of the virtual return for stock i; and 'corr' and 'var' are the correlation and variance operators, respectively. The observed returns processes are assumed to be covariance-stationary.

The maximal negative first order serial correlation for individual stock returns that is attributable to nontrading, according to Lo and MacKinlay, is given by:

$$\min_{(p_i)} \mathrm{corr}[R_{it}^{o}, R_{it+1}^{o}] = -\left(\frac{|\xi_i|}{1+\sqrt{2}|\xi_i|}\right)^2 \tag{7.5}$$

and it is attained at a nontrading probability given by:

$$p_i = \frac{1}{1+\sqrt{2}|\xi_i|}, \tag{7.6}$$

where $\xi_i \equiv \mu_i / \sigma_i$

All variables are as defined in equation (7.4) above.

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[4] This is the true (unobservable) continuously compounded return given by a primitive return-generating process, $R_{it} = \mu_i + \beta_i \Lambda_t + \varepsilon_{it}$ for $i = 1, \ldots, N$, where Λ_t is some zero-mean serially independent and identically distributed common factor and ε_{it} is zero-mean idiosyncratic noise that is temporally and cross-sectionally independent at all leads and lags.

The results (see Appendix I) support the proposition by Lo and MacKinlay that nontrading induces negative serial correlation in individual security returns with nonzero mean and that the smaller the mean, in absolute terms, the closer the autocorrelation is to zero. For example, RDC in Botswana with a nontrading probability of 89.8 percent exhibits significant first order serial correlation (at the 5% level) for the entire return series of -11.4 percent. However, due to the small mean return of -0.003 percent and a relatively large variance of 0.040 percent, the first order serial correlation induced by nontrading is almost zero. The maximal negative serial correlation induced by nontrading for this stock is also very small, almost zero and is attained at a probability of nontrading very close to 100 percent (that is, 99.8 percent).

Another stock on the same market, FNB, with a moderate thin trading of 50.6 percent but a high mean return of 0.181 percent and relatively small variance of 0.019 percent, has an insignificant first order serial correlation coefficient of 5.4 percent. However, the absolute first-order serial correlation induced by nontrading for this stock is relatively high (-0.851 percent). The maximal negative nontrading-induced serial correlation for FNB is also relatively high (-1.237 percent) and it is attained at a relatively low probability of nontrading of 84.3 percent in comparison to the other stocks.

Overall the results show that the autocorrelation induced by nontrading does not exceed 1 percent in absolute terms for stocks on all markets, except PHC on the BRVM with a nontrading-induced autocorrelation of -1.331 percent. Mauritius, on whose sample the random walk hypothesis was rejected, irrespective of which method of measuring returns is used, shows that there is insignificant nontrading-induced autocorrelation in all the stocks. Therefore the deviation from the random walk by the stocks on the Mauritius market is not necessarily due to thin trading, but other pricing inefficiencies.

7.5 Remarks and conclusions

In this paper, thin trading on African stock markets was investigated and found to be an extensive problem. The thin trading observed suggests that investors who intend to benefit from short-term price fluctuations may not find the Namibian Stock Exchange and quartile 4 stocks for the other markets in this study favourable. Due to thin trading, investors may be forced to hold stocks even at a time when they want to close their positions or get out of the market. The three different return measurement methodologies presented in the paper produce different correlation coefficients and Z-values suggesting differences in the random walk test results. Our findings also tend to suggest that the contradictory evidence in the random walk tests of certain African stock markets could be partly a methodology problem, especially in a thinly traded market environment.

The findings using the Lo and MacKinlay model also support the literature that the serial correlation induced by thin trading is only minimal in individual stock returns, which may not be the case for portfolio (or index) returns. This observation throws more doubt on the evidence from African stock markets, where previous studies used index data without adjustments for thin trading. Where individual stock returns were used, the effect of thin trading on the results is relatively minimal. Therefore, future research on African stock markets should make use of individual stock returns data and/or make proper adjustments for thin trading, especially when index returns are used.

There is also need for a consensus on the best practice of addressing thin trading in the random walk tests using individual stock returns. At the moment, the consensus seems to indicate that the widely acclaimed TOT approach and its variant, the ATT approach, are the best adjustment methods currently available where individual stock returns are concerned.

8 OUT-OF-SAMPLE PREDICTABILITY OF AFRICAN STOCK MARKET INDICES: A COMPARISON OF LINEAR TO NONLINEAR MODELS

8.1 Introduction

Researchers in emerging markets are increasingly doubtful about the relevance of linear models in testing the Efficient Market Hypothesis (EMH). Stock prices are believably generated by some chaotic dynamics leading to nonlinear dependencies. Such nonlinear dependencies are believed to be more likely in emerging markets than developed markets. This perception emanates from the knowledge that emerging markets have characteristics that are relatively different from those of their developed counterparts. Developed markets are relatively big in size, exhibit high levels of liquidity and active trading, and have fewer institutional and regulatory impediments. They are also characterised by sophisticated and well-informed investors who respond to information more instantaneously. The opposite is, unfortunately, true for most emerging markets. This explains the assertion by Harvey, *et al.* (2000) that emerging markets provide a good testing ground for the viability of nonlinear forecasting techniques.

The use of linear models in testing the EMH is justified, *inter alia*, by the assumption that investors are rational, risk-averse, unbiased in their forecasts and respond promptly to price sensitive information. However, according to Antoniou, *et al.* (1997), Asal (2000) and Appiah-Kusi and Menyah (2003), the use of a linear model in testing the EMH, when the underlying return generating process is nonlinear, results in the hypothesis of no predictability being wrongly accepted. Standard tests of market efficiency such as the autocorrelation and runs tests are said to lack power in accepting or rejecting the EMH if deterministic chaos rather than a stochastic process generates stock returns. These tests are incapable of capturing nonlinearities resulting in inappropriate inferences being drawn. They also assume that both the mean and standard deviation of stock returns are constant over the estimation period. Contrary to these assumptions, financial asset returns have changing conditional variances with deterministic and stochastic components (e.g. Korkie, *et al.*, 2002).

Nonlinearities in stock returns are believed to be mostly induced by investor psychology[1] and behaviour, such as when investors overreact to bad news and under-react to good news (see Appiah-Kusi and Menyah, 2003; Asal, 2000; DeBondt and Thaler, 1985). These nonlinearities would arise through a feedback mechanism of returning the asset price to its equilibrium level (Appiah-Kusi and Menyah, 2003). Investors may only trade when it is economically profitable to do so due to transaction costs, resulting in lagged responses. The lagged responses may also be a result of the wait-and-see attitude among investors, prevalent in small order-driven markets, as they wait for other investors to reveal their preferences. This tallies with the explanation by Sarantis (2001) that nonlinearities and cycles in stock prices can be attributed to the diversity in agents' beliefs, heterogeneity in investor objectives, and herd behaviour. This information asymmetry is also believed to be more serious in emerging markets, resulting in uninformed investors delaying their responses in order to imitate investors with more information.

Evidence on the efficiency of African stock markets, although marred with contradictions[2], tends to suggest that the markets generally deviate from the random walk. African markets that have been found to deviate from the random walk include Mauritius (Bundoo, 2000; Mlambo and Biekpe, 2003; Smith, *et al.*, 2002), Egypt (Asal, 2000; Smith, *et al.*, 2002), Morocco (Smith, *et al.*, 2002), Botswana and Nigeria (Appiah-Kusi and Menyah, 2003; Smith, *et al.*, 2002), Kenya and Zimbabwe (Smith and Jefferis, 2002; Smith, *et al.*, 2002), Ghana (Appiah-Kusi and Menyah, 2003; Mlambo and Biekpe, 2003), the Ivory Coast, South Africa and Swaziland (Appiah-Kusi and Menyah, 2003). In Magnusson and Wydick (2002), all the eight African stock markets in the study could not conform to the strongest of the random walks, the random walk 1. This inefficiency of African stock markets implies that one

[1] Price sensitive, but less frequent, macroeconomic news such as money supply, inflation and interest rates are also said to contribute to nonlinearities, especially in short horizon returns.

can exploit patterns in historical stock prices or returns to predict future values and thus make abnormal gains. Where some markets have been found to be consistent with the random walk, the results have been critiqued by the suggestion that the return generating processes for these markets could be nonlinear such that linear models are incapable of detecting the predictability.

Most studies on African stock markets have concentrated on in-sample predictability. No efforts have been made to investigate if this predictability can also be observed in out-of-sample data. This has particular interest since in practice the aim is to predict future unknown values.

This chapter attempts to meet two objectives: (1) It investigates if stock returns can be predicted ex-post by estimating the prediction model using pre-sample data and forecasting on out-of-sample data. (2) It compares the performance of nonlinear to linear models in making the ex-post forecasts. Where a nonlinear model performs better in forecasting, this could imply that the return generating process on the specific market is nonlinear and the reverse is true for a linear model.

8.2 The nonlinear modelling techniques

The growing evidence that financial time series data is consistent with nonlinear return generating processes has resulted in the emergence, and adoption, of nonlinear modelling techniques in stock markets. Nonlinear models include the chaotic dynamics, turbulent motions, the neural networks, technical trading rules and GARCH-type models (Fernández-Rodríguez, *et al.*, 1999). The most common are the chaos models, which attempt to identify deterministic or predictable nonlinear dynamic processes from apparently random price movements. The advancement in computer technology has made it possible to model these sophisticated nonlinear processes.

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[2] The contradictions could be a result of the different periods being investigated with some periods containing structural breaks in the time series and others being purely stochastic.

Some nonlinear modelling techniques include incorporating heterogeneous beliefs, adaptive beliefs and herd behaviour in the return generating models (Shively, 2003). A good example is presented in Kiselev, *et al.* (2000). Kiselev, *et al.* used a nonlinear stochastic dynamic system that assumes two types of traders, random and technical. While the random traders buy, sell or wait with an equal probability of 1/3, the intelligent traders use 'Bollinger Bands' in deciding whether to buy, sell or wait. If the next price prognosis is lower than the lower band, the trader considers the security oversold and places a buy order. If the prognosis is higher than the upper band, the trader expects the price to drop and places a sell order. If the predicted price falls within the Bollinger Bands, the trader keeps his current position unchanged. According to Kiselev, *et al.*, the rationale for the strategy is that the real price of the asset is a stochastic walk around the fundamental or fair value. These traders profit from basing their trades on the deviation of the prices from this fair value.

Using simulation, Kiselev, *et al.* demonstrated that trade occurs between members of the same group most of the time and that technical traders rarely participate in the market or change their positions while random traders constantly exchange money for shares. The results also suggested that trades by technical traders affect the time dependent equilibrium price, which, in their study, was assumed to behave similarly to the actual price. While technical traders continue to increase their cash inventory during both bull and bear markets, random traders continuously lose theirs. During the bull market, technical traders were found to hold more shares than cash, while the reverse is true for random traders.

The nonlinear modelling technique that is gaining popularity by the day is the artificial neural network. Harvey, *et al.* (2000) defined neural networks as systems, first devised in research on artificial intelligence, in which a computer learns the nonlinear relationship between independent and dependent variables through analysis of large quantities of data. Given out-of-sample data, neural networks are believed to predict the outcome of a nonlinear function more accurately than linear models. However, according to Harvey, *et al.* (2000), although the neural net is able to discern nonlinear relationships and to provide more predictive power in factors that may be considered useless in a linear model, it has its own limitations, which include the following: (1) Since the underlying function is neither prescribed nor predicted explicitly, the user is completely unaware of the closed form relationship that the neural net would have learned making it difficult to model human intuition. (2) It requires large quantities of data, which is problematic in young markets (such as those in Africa), and where records of daily data, or even weekly data, are not available. (3) The numerous data points required by the technique can result in over fitting of the model. (4) The benefits from using the neural net as a trading mechanism are also potentially eliminated by the high transaction costs in emerging markets (Harvey, *et al.,* 2000: 1 – 2). According to Deco, *et al.* (1997), for a neural network to perform better, it requires training on a set of data that contains the underlying structure to be discovered, ignoring regions with only a noisy behaviour.

Other nonlinear models that have been used in the literature include the threshold modelling techniques, which could be linear within a particular regime but nonlinear across regimes. A specific example is the three-regime, nonlinear threshold random walk model used by Shively (2003). He argued that the idea behind the model is that investors can trade stocks in all three regimes, but they have the added incentive of selling (buying) stocks after unusually large positive (negative) returns. Stock market frictions such as transaction costs, capital gains taxes, liquidity constraints and short-selling restrictions, stock market bubbles, and stock market risk were used to determine the two threshold return-values separating the three stock market regimes. Shively argued that transaction costs tend to create symmetric threshold values whereas the other frictions cited above tend to create asymmetric threshold values. One variant of the threshold models is the nonlinear momentum threshold autoregressive (MTAR) model used by Bohl (2002) to empirically investigate the existence of periodically collapsing bubbles in US stock markets.

Oh and Kim (2002) proposed a stock trading model based on chaotic analysis, and piecewise nonlinear models. They argued that a piecewise nonlinear model using structural changes has been known to significantly improve the performance for time series forecasting. The technique is modelled in four phases. The first phase involves selecting the time-lag size for input variables based on chaos theory. The second phase involves conducting the nonparametric statistical test to construct a homogenous group. The third phase involves applying back propagation neural networks (BPN) to forecast the change-point group. The final phase uses the BPN to forecast the output.

Another set of nonlinear models is the nearest neighbour (NN) predictors. Fernández-Rodríguez, *et al.* (1999) suggested that the nearest neighbour can be thought of a generalisation of technical trading rules, whereby sections of past time series data might have resemblance to sections of future time series data. These nonlinear deterministic forecasting models are described by Cao and Soofi (1999) as time-delay embedding techniques with a local linear predictor.

In a book review, Öller (2003) poses the question as to why a forecaster should be interested in nonlinear modelling. He suggested the possible explanation to be the poor performance in real forecasting of models that are optimal in a linear world. In the presence of structural breaks in a time series, a linear forecasting model breaks down and successfully estimating a new model would only be possible when there is sufficient new data available. If such structural breaks can be modelled nonlinearly, then the nonlinear model should be able to forecast such breaks or at least adapt quickly (Öller, 2003).

8.3 Evidence of nonlinearities in financial time series

There is an increasing amount of evidence in support of the assertion by Korkie, *et al.* (2002) that most economic series, including financial asset returns, exhibit nonlinearity, structural shifts and heteroskedasticity. Korkie *et al.* found evidence in support of a nonlinear return generating model, a product of a model for forecasting return signs and a model for forecasting return magnitudes. The information instruments used in their predictions include interest rates; yield curve spreads, and dividend yields. They also claimed their results to be supportive of existing linear stock return forecasting models for in-sample predictability. There was, however, poor external (out-of-sample) validity of the linear prediction models, which they attributed to nonstationarity. They suggested that a possible explanation could be that the return-generating model is nonlinear. Using the Brock, *et al.* (1996) test for nonlinearity, they found the model for stock returns to be nonlinear, when economic variables are excluded.

The findings by Korkie, *et al.* (2002) were consistent with those of Hsieh (1991). Hsieh (1989, 1991) found evidence of strong nonlinear dependence in daily exchange rate changes and stock returns, respectively. He argued that this nonlinear dependence was largely exerted through the variance rather than the mean of the series and was induced by conditional heteroskedasticity. He suggested the use of flexible ARCH-type models (e.g. GARCH) to capture this nonlinearity in stock returns.

Sarantis (2001) used the smooth transition autoregressive (STAR) model instead, arguing that studies that apply the GARCH models typically use daily or high frequency data whereas his focus was to investigate potential nonlinearities and cyclical movements in stock prices using annual stock price growth rates. Sarantis (2001) found evidence to reject linearity in stock price growth rates for the seven developed markets he studied. The nonlinear STAR-based models generally performed better than the linear autoregressive and random walk models in forecasting stock price growth rates.

Harvey, *et al.* (2000) investigated whether returns in emerging markets can be forecast better using neural networks instead of linear prediction models. The assertion was that many of the factors that are believed to drive financial markets might not be related by linear functions. They found that the neural network outperforms the buy-and-hold strategy in forty-four of the fifty-four country years they studied. The neural net also produced a lower volatility than the buy-and-hold strategy in all the country years. Overall, the neural networks outperformed both the buy-and-hold and regression benchmarks. According to Harvey, *et al.*, the evidence indicated that volatility of a portfolio is lowered and returns are increased when using the neural network as a trading strategy.

Eakins and Stansell (2003) examined whether neural networks could be used to perform forecasts, based on a set of financial ratios reflecting traditional value-based investment strategies, to earn superior investment returns. The argument was that if some stocks provide higher returns (less risk) than do others, then the financial markets are not efficient and the CAPM is not valid. They chose the neural network model because of its proven record of detecting relationships between dependent and independent variables that are highly nonlinear. They found the average return for the neural network portfolio to be greater than for the alternative models (a 20-year average of 17.09 percent). Their findings showed an investment of US$1 in 1977 growing to US$18.70 in 1997 with the neural network portfolio of value firms, while it grew to less than US$8 with the alternative portfolios. Their results also confirmed the literature suggesting that value stocks provide higher returns with lower risk than can be obtained from a random walk process. The Sharpe ratio was highest for the neural network portfolio.

Cao and Soofi (1999) used the time-delay embedding techniques of a local linear predictor to make out-of-sample predictions of five dollar-exchange rates, namely, the Canadian dollar, British pound, German mark, Japanese yen and French franc. Their predictions outperformed the mean value predictor for the pound/dollar and yen/dollar rate returns but not for the other three exchange rate returns. Using a technique of nonlinear dynamics, they found all the exchange rate return series to have very high embedding dimensions ranging from 27 for the Mark/$ to 56 for the yen/$ rate returns. They took the evidence to indicate that these series are generated by high dimensional systems with measurement noise or by high dimensional nonlinear stochastic systems (nonlinear deterministic systems with dynamic noise).

Fernández-Rodríguez, *et al.* (1999) applied simultaneous nearest neighbour (SNN) predictors to nine European Monetary System (EMS) currencies' exchange rates to the German mark. Using the Brock-Dechert-Scheinkman (BDS) test statistic, the null hypothesis that the series are independently and identically distributed was rejected suggesting nonlinear dependencies. When measuring the forecasting performance of the models using the Theil's U statistic, the nonlinear SNN predictors performed marginally better than both a random walk (RW) and the traditional ARIMA predictors. The findings also suggested that the probability of correctly predicting the sign of change is higher for the SNN predictors than for the ARIMA case. Using the

Diebold-Mariano test for forecast accuracy, the SNN predictor outperformed the RW and ARIMA models at the 1% level in 8 out of 9 and 3 out of 9 cases, respectively.

Shively (2003) tested the linearity of the six international stock indices; the CAC 40, DAX 30, FTSE 100, Nikkei 225, S&P 500 and TSE 300, using Tsay's (1998) chi-square test [3] and found all six indices to be highly consistent with threshold nonlinearity. He used Tsay's (1998) threshold modelling technique to partition each stock price index into three regimes. With the three-regime nonlinear threshold random walk model, Shively (2003) found statistically significant evidence that stock prices are consistent with a regime-reverting process, where, on average, stock prices in the outer regimes revert to the middle regime.

Oh and Kim (2002) found that the piecewise nonlinear model they proposed perform better than the buy-and-hold strategy and the basic BPN in predicting the KOPSI 200 stock price index. Bohl (2002), using the nonlinear MTAR model, found periodically collapsing bubbles in the US stock markets for the 1871 to 2001 sample period. All this evidence of nonlinearities in financial time series data is motivation enough for the extension of similar investigations to the uniquely structured African stock markets.

8.4 Data and preliminary results

In this study, the out-of-sample predictability of daily African stock market indices is investigated. The indices are obtained from the respective stock exchanges. The periods of analysis vary from one market to the other, depending on data availability and the age of the market. The longest period of analysis is for Egypt, Morocco and Zimbabwe, ranging from January 1997 to December 2002. For the Bourse Regionale des Valeurs Mobilieres (BRVM), the West African Regional Exchange in Cote d'Ivoire, the sample period is restricted to 16 September 1998 to 9 November 2001. This is because the market shifted from trading three times a week to trading daily

[3] The test detects threshold nonlinearity using arranged autoregression, recursive least-squares estimates, and predictive residuals.

thus introducing a structural break in the series. The period before the shift is, therefore, chosen because it has more data points.

Mauritius also shifted from trading three times a week to trading daily in 1997. For this market, the period of investigation is, therefore, restricted to 24 November 1997 to 31 December 2002. In the final samples, all the markets covered were trading daily for the periods investigated except Ghana and the BRVM.

8.4.1 Stationarity

The data is tested for stationarity using the Augmented Dickey Fuller (ADF) test for unit roots. This is important if reliable forecasts are to be obtained from parametric models. The ADF test is applied to the log levels of the indices and their first differences with and without a linear time trend. The BRVM-10, BRVM-C, Ghana Stock Exchange (GSE)[4], and Morocco's CFG25 indices reject the unit root tests at the 5% level of significance (see Table 8.1). Apart from these indices, the ADF test results indicate nonstationarity in the index log levels. The series, however, become stationary after first differences. Therefore, the first differences of the index log levels are used in the estimations.

Except for Botswana's Foreign Companies Index (FCI) and All Companies Index (ACI), and Zimbabwe's Mining Index, the indices have lag lengths of at least one. The implication of this is that the error terms are autocorrelated and thus not independently distributed.

8.5 Methodology

The predictability of African stock indices is investigated using different forecasting models, that is, the Autoregressive Integrated Moving Average (ARIMA) model, an Exponential Feedback Autoregressive (EFAR) model and the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model.

[4] The GSE index also exhibits stationarity in the log levels, at the 5% level of significance, using the ADF with a constant intercept.

Table 8.1: Unit root tests for stationarity

Country/ Stock Exchange	Stock Market Index	# Obs.	Log Levels								First Differences							
			With Constant				With Constant and Linear Trend				With Constant				With Constant and Linear Trend			
			Lag length	max lag	ADF-stat	Prob.	Lag length	max lag	ADF-stat	Prob.	Lag length	max lag	ADF-stat	Prob.	Lag length	max lag	ADF-stat	Prob.
Botswana	ACI	1177	1	22	-1.438	0.565	0	22	-2.586	0.287	0	22	-36.813**	0.000	0	22	-36.803**	0.000
	DCI	1177	4	22	-1.105	0.716	4	22	-1.595	0.795	3	22	-12.029**	0.000	3	22	-12.049**	0.000
	FCI	1177	1	22	-1.505	0.531	0	22	-2.673	0.248	0	22	-36.823**	0.000	0	22	-36.813**	0.000
BRVM	BRVM10	752	2	17	-1.522	0.522	3	17	-3.493*	0.041	2	17	-9.192**	0.000	2	17	-9.182**	0.000
	BRVM_C	752	3	17	-1.604	0.480	3	17	-3.828*	0.016	2	17	-9.003**	0.000	2	17	-9.001**	0.000
Egypt	EFGI	1489	3	23	-0.422	0.903	3	23	-2.420	0.369	1	23	-25.483**	0.000	1	23	-25.494**	0.000
	HFI	1489	3	23	-0.539	0.881	3	23	-2.549	0.304	2	23	-19.227**	0.000	2	23	-19.232**	0.000
Ghana	GSE	753	6	19	-3.022*	0.033	6	19	-3.422*	0.049	5	19	-6.480**	0.000	5	19	-6.482**	0.000
Mauritius	SEMDEX	1401	2	22	-1.307	0.628	2	22	-3.041	0.122	1	22	-17.519**	0.000	1	22	-17.528**	0.000
	SEMTRI	1401	2	22	-2.433	0.133	2	22	-2.570	0.294	1	22	-17.355**	0.000	1	22	-17.351**	0.000
Morocco	CFG25	1493	1	23	-0.926	0.780	1	23	-3.443*	0.046	0	23	-26.081**	0.000	0	23	-26.457**	0.000
Namibia	LOCAL	1459	1	23	0.736	0.993	1	23	-2.890	0.166	0	23	-56.936**	0.000	0	23	-57.035**	0.000
	OVERALL	1459	1	23	-1.606	0.479	1	23	-2.196	0.491	0	23	-45.445**	0.000	0	23	-45.429**	0.000
Tunisia	BVMT	1249	3	22	-1.600	0.482	3	22	0.525	0.999	2	22	-19.743**	0.000	2	22	-19.972**	0.000
	TUNINDEX	1249	3	22	-1.247	0.656	3	22	-0.403	0.987	2	22	-18.113**	0.000	2	22	-18.174**	0.000
Zimbabwe	INDUSTR	1499	1	23	1.804	1.000	1	23	-0.957	0.948	0	23	-27.620**	0.000	0	23	-27.795**	0.000
	MINING	1499	0	23	1.462	0.999	0	23	-1.543	0.814	0	23	-37.240**	0.000	0	23	-37.439**	0.000

* Significance at the 5% level
** Significance at the 1% level
Significance implies stationarity
Lag length based on the Schwarz Information Criterion
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Each model is benchmarked with the random walk (RW) model with drift. While both the EFAR and GARCH models can be considered nonlinear, the former is nonlinear in the conditional mean while the latter is nonlinear in the conditional variance.

For the ARIMA model, two specifications are considered. The first is a parsimonious, under-parameterised, ARIMA (1,1,0), which, henceforth, is simply referred to as the autoregressive (AR) model. The second is an over-parameterised ARIMA (p,1,q) model, which, henceforth, is simply referred to as the ARMA model. The model is uniquely identified for each index using the partial autocorrelation function (PACF) for lags 1 up to 30, the Schwarz Information Criterion and the absence of serial correlation in the residuals. The autoregressive and moving average terms (p's and q's) that enter the model depend on the significant coefficients of the PACF (see Table 8.2). Where the autocorrelation coefficients are significantly different from zero, the term is included as an autoregressive (AR) term. After including the identified autoregressive terms, the regression is rerun and tested for autocorrelation in the residuals, for lags 1 up to 30. Any significant autocorrelation coefficients for the residuals are included as moving average (MA) terms. The final model specification for each index is based on the Schwarz Information Criterion and the absence of serial correlation in the residuals. The specific equations estimated are given in Appendix J.

8.5.1 The nonlinear models

Two nonlinear models are used, the GARCH-M and the EFAR model. The goal for using these nonlinear models is to determine if the acceptance of the RW hypothesis on some African markets is because the return-generating processes are nonlinear such that the RW model fails to detect the patterns in the time series. Recent studies on African stock markets have used the GARCH family of models to model nonlinearities in stock prices (e.g. Appiah-Kusi and Menyah, 2003; Asal, 2000; Smith and Jefferis, 2002). The argument is that the nonlinearities observed in price series are in the conditional variance of the stock returns rather than in the conditional mean. The GARCH-M model is, therefore, used as one of the nonlinear model specifications for the ensuing forecasts.

Table 8.2: Test for serial correlation using the PACF

Exchange	Botswana			BRVM		Egypt		Ghana	Mauritius		Morocco	Namibia		Tunisia		Zimbabwe	
Index	ACI	DCI	FCI	BRVM10	BRVM_C	EFGI	HFI	GSE	SEMDEX	SEMTRI	CFG25	LOCAL	Overall	BVMT	Tunindex	Industrial	Mining
std. err.	*0.03*	*0.03*	*0.03*	*0.048*	*0.048*	*0.026*	*0.026*	*0.037*	*0.029*	*0.029*	*0.026*	*0.026*	*0.026*	*0.029*	*0.029*	*0.026*	*0.026*
Lag 1	-0.085*	0.094*	-0.085*	0.097*	0.196*	0.257*	0.292*	0.203*	0.383*	0.356*	0.362*	-0.322*	-0.181*	0.416*	0.239*	0.311*	0.023
2	-0.026	0.114*	-0.027	0.136*	0.167*	-0.086*	-0.111*	0.105*	0.102*	0.133*	0.038	-0.115*	0.031	-0.074*	0.116*	0.065*	0.030
3	0.039	0.033	0.037	0.128*	0.137*	0.075*	0.096*	0.159*	0.027	0.019	0.003	-0.034	0.021	-0.124*	-0.082*	0.056*	0.017
4	-0.072*	0.213*	-0.072*	0.023	0.007	0.033	0.043	0.169*	-0.056	-0.050	-0.002	-0.019	-0.005	0.047	-0.051	-0.025	-0.019
5	0.032	0.046	0.030	-0.006	0.015	0.012	0.006	0.086*	-0.019	-0.041	0.067*	0.007	-0.053*	0.018	-0.004	-0.048	0.039
6	0.000	0.057	-0.002	-0.038	-0.029	-0.042	-0.058*	0.112*	-0.022	-0.018	-0.057*	0.017	-0.008	0.032	0.026	0.003	0.042
7	-0.044	0.030	-0.043	-0.045	-0.035	-0.034	-0.031	-0.006	0.077*	0.082*	0.042	0.006	0.032	0.039	0.024	0.039	0.021
8	-0.040	0.099*	-0.039	-0.045	-0.064	-0.022	-0.023	-0.043	0.016	0.015	0.035	0.032	-0.006	0.026	0.026	0.004	-0.007
9	0.082*	0.031	0.080*	-0.098*	-0.039	0.026	0.036	0.027	0.048	0.052	0.019	-0.030	0.016	-0.053	-0.005	0.014	0.009
10	0.008	0.098*	0.006	-0.044	-0.070	0.037	0.037	0.073	0.037	0.046	0.010	0.023	-0.001	0.106*	0.030	0.024	0.032
11	-0.057	0.008	-0.061	0.048	0.040	0.028	0.040	0.017	0.029	0.019	0.030	0.002	0.012	0.061*	0.080*	0.010	-0.014
12	0.011	-0.006	0.011	0.028	-0.038	0.041	0.031	-0.013	0.019	0.027	-0.005	-0.001	0.022	0.022	0.042	-0.005	-0.046
13	-0.016	0.014	-0.016	-0.035	0.004	-0.024	-0.021	-0.072	0.031	0.021	0.036	-0.010	0.012	0.025	0.057	0.008	-0.006
14	-0.028	-0.011	-0.028	-0.032	-0.008	-0.019	-0.015	0.061	0.003	0.013	0.039	-0.002	0.021	0.014	0.010	-0.018	-0.011
15	0.088*	-0.005	0.087*	0.044	0.038	-0.025	-0.006	-0.007	0.019	0.020	0.015	-0.002	0.034	-0.029	-0.023	0.031	-0.018
16	0.036	0.033	0.038	0.005	-0.024	0.051	0.039	-0.047	0.062*	0.054	-0.022	0.031	-0.008	-0.001	-0.014	0.024	0.025
17	-0.016	0.012	-0.016	-0.021	0.001	0.019	0.023	-0.057	0.013	0.017	-0.007	-0.001	-0.044	-0.005	0.039	0.027	0.019
18	-0.043	0.010	-0.043	-0.046	-0.124*	0.001	0.000	0.000	0.021	0.028	0.004	0.014	0.038	0.019	0.000	-0.006	-0.026
19	-0.006	-0.026	-0.006	-0.093	-0.038	-0.007	-0.017	-0.080*	-0.026	-0.027	0.007	-0.024	-0.022	-0.022	-0.027	-0.046	-0.020
20	0.009	0.002	0.011	0.007	-0.077	-0.023	-0.005	-0.022	-0.026	-0.028	0.009	0.015	0.035	-0.038	-0.061*	-0.008	0.008
21	0.057	-0.067*	0.057	-0.094	-0.071	-0.024	-0.031	-0.020	-0.056	-0.066*	0.023	0.007	0.050	-0.049	-0.034	-0.002	-0.020
22	0.021	0.018	0.022	0.011	-0.006	-0.029	-0.021	-0.008	-0.074*	-0.080*	0.036	0.006	0.018	-0.008	-0.009	-0.014	0.020
23	-0.015	-0.007	-0.014	-0.051	-0.038	-0.034	-0.028	-0.039	0.011	0.019	-0.009	0.024	0.025	-0.007	-0.015	-0.015	0.036
24	-0.052	0.017	-0.051	-0.044	-0.014	-0.020	-0.032	-0.023	-0.010	-0.016	-0.018	0.024	-0.022	0.057	0.022	-0.016	-0.008
25	0.043	0.031	0.042	0.030	0.075	-0.083*	-0.059*	0.060	0.029	0.031	-0.018	0.005	0.022	0.019	-0.020	-0.024	-0.046
26	0.043	-0.011	0.043	0.053	0.018	0.007	0.002	-0.001	0.025	0.025	0.000	-0.011	-0.004	0.006	0.003	0.037	0.040
27	-0.010	0.002	-0.009	-0.007	0.010	0.062*	0.062*	0.033	0.018	0.013	-0.047	0.014	-0.065*	0.014	-0.020	0.003	-0.025
28	-0.006	-0.009	-0.006	-0.022	-0.009	0.008	0.019	0.015	-0.034	-0.038	0.033	-0.005	0.020	0.026	0.001	-0.013	-0.014
29	0.016	0.010	0.016	-0.069	-0.050	0.018	-0.013	0.014	-0.014	0.003	0.013	-0.003	0.020	0.031	-0.014	-0.005	0.014
30	-0.069*	-0.021	-0.069*	0.037	0.002	0.046	0.065	0.020	-0.054	-0.025	0.028	-0.011	-0.048	0.014	0.008	0.011	-0.033

* Implies the coefficient is twice the standard error (significance at the 5% level)
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

8.5.1.1 The EFAR model

The EFAR model is a slight modification of the the Smooth Transition Autoregressive (STAR) models originally developed by Teräsvirta and Anderson (1992) to model nonlinearities over the business cycle of industrial production, and used to model and forecast stock growth rates by Sarantis (2001). While the uniqueness of STAR models is in measuring regime transitions or cyclical movements, the EFAR is used to measure the feedback mechanism of the price reverting back to its equilibrium level. The transition functions for the STAR models are, therefore, replaced by an exponential feedback component. In addition, while the STAR models use growth rates, the EFAR uses continuously compunded returns in estimating the model.

The EFAR of order *p*, for variable R_t is specified as follows:

$$R_t = \beta_0 + \boldsymbol{\beta_1}'\boldsymbol{x}_t + (\theta_0 + \boldsymbol{\theta_1}'\boldsymbol{x}_t)F(R_{t-d}) + u_t \qquad (8.1)$$

where $\boldsymbol{x}_t = (R_{t-1}, R_{t-2}, ..., R_{t-p})'$, $\boldsymbol{\beta_1} = (\beta_1, \beta_2, ..., \beta_p)'$, $\boldsymbol{\theta_1} = (\theta_1, \theta_2, ..., \theta_p)'$, $u_t \sim nid(0, \sigma^2)$

F is a feedback function, R_{t-d} is a 'feedback' variable, and d is a delay parameter. The feedback function[1] is specified as follows:

$$F(R_{t-d}) = -\exp(-R_{t-d}^{\gamma}) \qquad (8.2)$$

where $-1 \le R_{t-d} \le 1$ [2] and γ is the power of the exponent and is restricted to 1, 2 and 3 [3].

[1] Please note that this feedback function is only novel and has not been theoretically proven to be an optimal function for this purpose.

[2] For $R_{t-d} > 1$, the function approaches 0 and takes the value of 0 for large R_{t-d}. For $R_{t-d} < -1$, the function approaches negative infinite for odd numbered γ s (i.e. 1 and 3) and approaches 0 for even numbered γ s (i.e. $\gamma = 2$).

[3] Since R_{t-d} can either be negative or positive, the feedback function is mostly undefined for $R_{t-d} < 0$ when γ is a fraction (non-discrete). Even-numbered γ s produce structures with similar patterns and the same is true for odd-numbered γ s. However, as γ becomes large, the values of the function approaches one for $-1 < R_{t-d} < 1$, and becomes constant at one, for very large γ s. Therefore, γ is assumed to take discrete values of 1, 2 and 3.

The same process in building the STAR models is used to build the EFAR model. The first step is to specify a linear autoregressive (AR) model. Linearity is tested against the EFAR model by estimating an auxiliary regression model as follows:

$$R_t = \beta_0 + \boldsymbol{\beta_1}' \boldsymbol{x}_t + \boldsymbol{\beta_2}' \boldsymbol{x}_t R_{t-d} + \boldsymbol{\beta_3}' \boldsymbol{x}_t R_{t-d}^2 + \boldsymbol{\beta_4}' \boldsymbol{x}_t R_{t-d}^3 + w_t \qquad (8.3)$$

Where $w_t \sim nid(0, \sigma_w^2)$

The linearity test is $H_0 : \boldsymbol{\beta_2}' = \boldsymbol{\beta_3}' = \boldsymbol{\beta_4}' = 0$.

The delay index, *d*, is then specified by testing Equation (8.3) for a wide range of values, $1 \le d \le D$. In cases where linearity is rejected for more than one value of *d*, *d* is chosen by $d = \arg\min\ p(d)$ for $1 \le d \le D$, where *p(d)* is the p-value of the linearity test. An upper bound of *D* suggest that *d* should take values only for which autocorrelation was tested. In this case autocorrelation was tested for lags 1 to 30. This implies that $1 \le d \le 30$, that is, the upper bound is 30 lags.

After determining *d*, nested tests are used to determine the γ parameter (power of the exponent) for the feedback function (Equation 8.2).

The hypotheses for the nested tests are as follows:

$H_{04} : \boldsymbol{\beta_4} = 0$

$H_{03} : \boldsymbol{\beta_3} = 0 / \boldsymbol{\beta_4} = 0$

$H_{02} : \boldsymbol{\beta_2} = 0 / \boldsymbol{\beta_3} = \boldsymbol{\beta_4} = 0$

The p-values for all the F-tests of the above hypotheses are computed and γ is determined based on the lowest p-value. If the strongest rejection is for H_{04}, $\gamma = 3$ is selected, if for H_{03}, $\gamma = 2$ is selected, and if for H_{02}, $\gamma = 1$ is selected. The results and other important parameters leading to the unique specification of the EFAR model for each index are presented in Table 8.3.

Table 8.3: Specification of the nonlinear model[a]

Exchange	Index	k	LB(1)	LB(30)	Delay d	H_{04}	H_{03}	H_{02}	γ^{b}
Botswana	ACI	30	0.002	26.377	4	1.167×10^{-01}	4.966×10^{-05} *	5.601×10^{-04}	2
	DCI	21	0.379	31.611	4	8.857×10^{-02}	3.106×10^{-09}	9.898×10^{-14} *	1
	FCI	30	0.015	17.496	4	1.465×10^{-01}	1.184×10^{-04} *	1.878×10^{-04}	2
BRVM	BRVM10	10	0.002	17.080	1	1.198×10^{-07} *	2.148×10^{-03}	1.633×10^{-03}	3
	BRVMC	18	0.001	20.619	6	3.186×10^{-05}	4.644×10^{-02}	2.984×10^{-09} *	1
Egypt	EFGI	25	0.061	28.247	2	3.465×10^{-04}	4.423×10^{-08} *	9.225×10^{-04}	2
	HFI	27	0.011	22.013	2	1.023×10^{-03}	3.288×10^{-09} *	5.768×10^{-04}	2
Ghana	GSE	23	0.053	17.992	4	1.128×10^{-03}	4.634×10^{-12}	1.018×10^{-16} *	1
Mauritius	SEMDEX	22	0.011	27.568	6	1.989×10^{-06}	1.759×10^{-12} *	1.546×10^{-04}	2
	SEMTRI	22	0.006	30.318	6	1.841×10^{-04}	2.066×10^{-13} *	4.436×10^{-07}	2
Morocco	CFG25	6	0.025	15.847	6	3.234×10^{-03}	4.466×10^{-11} *	4.913×10^{-04}	2
Namibia	LOCAL	2	0.001	20.122	1	9.240×10^{-02}	3.488×10^{-10}	$0.000 \times 10^{+00}$ *[c]	1
	OVERALL	27	0.013	45.496	1	7.980×10^{-05}	$0.000 \times 10^{+00}$	$0.000 \times 10^{+00}$ *	1
Tunisia	BVMT	11	0.064	26.175	2	1.194×10^{-02}	6.669×10^{-08} *	4.862×10^{-03}	2
	TUNINDEX	20	0.741	18.594	1	1.028×10^{-07}	$0.000 \times 10^{+00}$ *	1.576×10^{-02}	2
Zimbabwe	INDUSTR	3	0.611	31.218	1	3.201×10^{-06}	$0.000 \times 10^{+00}$	$0.000 \times 10^{+00}$ *[c]	1
	MINING	1	0.002	29.736	1	2.806×10^{-01}	3.138×10^{-03} *	2.050×10^{-01}	2

[a] The values of the nested tests H_{04}, H_{03} and H_{02} are p-values.
* indicates the lowest or minimum p-value for the three nested tests.
[b] The power of the exponential ('feedback') function
[c] The lowest p-values were determined from the F-statistics
k is the maximum lag length based on the PACF
LB(v) is Ljung-Box statistic for the vth order autocorrelation of the autoregressive model.
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

8.5.2 Forecast evaluation measures

Each of the above models is estimated on a pre-sample and the estimates are then used to dynamically generate ex-post daily forecasts for the remaining 40 data points of the series (post sample). For dynamic forecasts, the sample is enlarged successively with the generated forecast values. The forecasting performance of each model is evaluated using four forecast error statistics[4], the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE), and the Theil Inequality Coefficient. In addition, a correct directional change index (D) is used to determine the frequency that the model successfully predicts the direction. These evaluation statistics are measured as follows:

$$RMSE = \sqrt{\sum_{t=T+1}^{T+h} \left(\hat{P}_t - P_t\right)^2 / h} \tag{8.4}$$

$$MAE = \sum_{t=T+1}^{T+h} \left|\hat{P}_t - P_t\right| / h \tag{8.5}$$

[4] All four statistics are reported because they are all automatically generated by Eviews when forecasting. If such forecast error statistics were to be calculated manually, reporting only one of them would have been enough.

$$MAPE = 100\sum_{t=T+1}^{T+h}\left|\frac{\hat{P}_t - P_t}{P_t}\right| \Big/ h \quad (8.6)$$

$$\text{Theil Inequality Coefficient: } U = \frac{\sqrt{\sum_{t=T+1}^{T+h}\left(\hat{P}_t - P_t\right)^2 / h}}{\sqrt{\sum_{t=T+1}^{T+h}\hat{P}_t^{\,2}/h} + \sqrt{\sum_{t=T+1}^{T+h}P_t^{\,2}/h}} \quad (8.7)$$

$$D = \sum_{t=T+1}^{T+h} D_t, \text{ where } \begin{cases} D_t = 1 & \text{if } (P_t - P_{t-1})\times(\hat{P}_t - \hat{P}_{t-1}) > 0, \\ D_t = 0, & \text{otherwise} \end{cases} \quad (8.8)$$

where $\hat{P}_t$ = forecasted index levels

P_t = actual index levels

h = number of forecast horizons

T = sample size for the estimation period

8.6 Empirical results

The results of the forecast evaluations as given by the RMSE, MAE and MAPE statistics are presented in Table 8.4. To enable easy comparison of forecasting performances of alternative models relative to the RW, the forecast error statistics for the alternative models are presented as ratios of the forecasting errors of the RW model.[5] Our forecasting samples are the last 40 data points of each index series.

The RMSE, MAE and MAPE statistics reported in Table 8.4 suggest that the AR and the EFAR models outperform the RW model in 14 out of 17, and 13 out of 17 indices, respectively. The results for the ARMA and GARCH are less appealing, with the two models outperforming the RW model in only 5 and 7 cases, respectively. The EFAR

[5] The other reason the statistics are presented as relative measures is because the RMSE and MAE depend on the scale of the dependent variable. Comparison of forecasts for the same series across different models is easier when presented as relative measures.

gives the best performance in forecasting the index levels in comparison to the RW model and alternative models, in 11 indices, while the AR gives the best performance in only three indices, the GSE Index, the BRVM-10 [6] and Morocco's CFG25 Index. The RW model outperforms the alternative models in only two indices, Botswana's FCI and ACI. The ACI and FCI are, however, highly correlated such that the results always tend to be identical. Graphs for the forecast values show that the patterns of the actual values of the two indices are almost identical for the forecast horizon (see Appendix K).

Darrat and Zhong (2000) suggested that if the stock prices follow a RW process, then the RW model should not be out-predicted by any other model. With this assertion, one can conclude that the FCI and ACI are best predicted by the RW. This is in line with the unit root test results presented in Table 8.1, where the two indices are first order integrated (have unit roots) with autocorrelated error terms. The results, however, support the assertion that under-parameterised (parsimonious) ARIMA models produce better forecasts than the over-parameterised variants. The over-parameterised ARMA only gives the best forecasts in one index, the BRVM-C, and outperforms the RW model in only 5 cases, as compared to 3 and 14 cases for the AR model[7].

The gains from using the EFAR model are quite high. Using the RMSE statistics, the gains from the EFAR model reach to as high as 64.71 percent over and above the RW model for the BVMT. For the remaining alternative models, the highest gain obtainable is 39.74 percent with the AR, 30.92 percent with the ARMA and 52.85 percent for the GARCH-M model. The EFAR model also gives gains over and above the AR as high as 24.97 percent for the BVMT. Attributing the performance of the EFAR model to its nonlinear specification is plausible in that, the model contains exactly the same autoregressive terms as in the ARMA model for most of the indices.

[6] Based on the RMSE error statistics

[7] It is important to note that the specification for the random walk model and the ARMA for Zimbabwe's Mining Index are the same since the ARMA has been identified using the PACF results, in which none of the coefficients are significant for this index.

Table 8.4: Dynamic out-of-sample forecast performance of alternative models relative to the RW model

Country/ Exchange	Stock market Index	AR			ARMA			EFAR			GARCH		
		$RMSE_{RW}$	MAE_{RW}	$MAPE_{RW}$	$RMSE_{RW}$	MAE_{RW}	$MAPE_{RW}$	$RMSE_{RW}$	MAE_{RW}	$MAPE_{RW}$	$RMSE_{RW}$	MAE_{RW}	$MAPE_{RW}$
Botswana	ACI	1.1011	1.1070	1.1067	1.3408	1.5840	1.5697	1.1585	1.3035	1.2956	1.6748	2.1170	2.0890
	DCI	0.9085	0.8984	0.8984	0.9654	1.0514	1.0494	0.7881*	0.8378*	0.8367*	0.9267	0.9965	0.9935
	FCI	1.1024	1.1088	1.1084	1.2923	1.5091	1.4955	1.1868	1.3301	1.3215	1.4833	1.8849	1.8553
BRVM	BRVM_10	0.9896*	1.0062	1.0057	1.1848	0.9769	0.9808	1.4566	1.4860	1.4837	1.0527	0.8272*	0.8312*
	BRVM_C	0.9974	0.9909	0.9915	0.8418*	0.7610*	0.7610*	0.9315	0.8482	0.8481	1.0397	1.0803	1.0832
Egypt	EFGI	0.7864	0.7863	0.7860	1.1172	1.0991	1.0971	0.6610*	0.6659*	0.6661*	0.9351	0.9416	0.9422
	HFI	0.7540*	0.7492*	0.7487*	1.1867	1.1505	1.1477	0.7754	0.7561	0.7542	0.8513	0.8605	0.8614
Ghana	GSE	0.8577*	0.8418*	0.8417*	3.4053	3.7196	3.7199	3.7059	3.8736	3.8635	3.7155	3.4389	3.4158
Mauritius	SEMDEX	0.6623	0.6767	0.6774	1.0288	1.0446	1.0453	0.6528*	0.6761*	0.6772*	0.8386	0.8282	0.8280
	SEMTRI	0.6915	0.7017	0.7022	1.0529	1.0881	1.0898	0.6714*	0.6939*	0.6951*	1.1256	1.1745	1.1769
Morocco	CFG25	0.6535	0.6502	0.6502	1.0193	1.0270	1.0274	0.5594*	0.5599*	0.5603*	0.9231	0.9343	0.9349
Namibia	LOCAL	0.7232	0.6434	0.6424	0.6908	0.6270	0.6263	0.4390*	0.3705*	0.3732*	0.4715	0.4470	0.4471
	OVERALL	1.1090	1.0609	1.0634	0.9247	0.9024	0.9037	0.7809*	0.7491*	0.7509*	1.8102	1.9785	1.9661
Tunisia	BVMT	0.6026	0.6053	0.6052	0.9719	0.9676	0.9678	0.3529*	0.3492*	0.3489*	1.3862	1.4011	1.4002
	TUNINDEX	0.7717	0.7734	0.7733	1.0064	1.0028	1.0028	0.6416*	0.6454*	0.6453*	0.8314	0.7955	0.7961
Zimbabwe	INDUSTRIAL	0.7210	0.7176	0.7188	1.0682	1.0563	1.0612	0.5203*	0.5053*	0.5045*	1.0178	1.0058	1.0109
	MINING	0.9708	0.9718	0.9707	1.0000	1.0000	1.0000	0.9077*	0.9125*	0.9075*	1.4482	1.4021	1.4364

RMSE = root mean squared error, MAE = mean absolute error, and MAPE = mean absolute percentage error
The subscript RW indicates the ratio of the forecast errors for the specified models to the forecast errors of the RW model. Values less than one indicate superior forecasting performance of the specified model relative to the RW model.
* Indicates the model with the best forecasting performance among all the models including the RW for each measure of forecasting error.
Note: The variables being forecast are the index levels, not the log levels or their first differences
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Therefore, the EFAR model seems able to capture the nonlinearities in the time series using as much information as in the ARMA. Observing from Botswana's FCI and ACI, the only weakness of the EFAR is that it fails to detect structural breaks in the forecasting horizon if the breaks do not form the underlying structure of the data in the estimation period. In other words, the EFAR fails to predict non-recurring surprises in a series.

Table 8.5: Out-of-sample forecast performance: Theil's U Inequality coefficients

Country/ Exchange	Stock market Index	RW	AR	ARMA	EFAR	GARCH
Botswana	ACI	0.021406*	0.023533	0.028455	0.024688	0.035265
	DCI	0.006243	0.005671	0.006042	0.004928*	0.005806
	FCI	0.022458*	0.024717	0.028792	0.026517	0.032855
BRVM	BRVM_10	0.006313	0.006250*	0.007452	0.009228	0.006610
	BRVM_C	0.004055	0.004046	0.003403*	0.003764	0.004196
Egypt	EFGI	0.026700	0.020930	0.029930	0.017558*	0.024937
	HFI	0.017203	0.012944*	0.020487	0.013331	0.014618
Ghana	GSE	0.003212	0.002754*	0.011022	0.012001	0.011796
Mauritius	SEMDEX	0.015215	0.010043	0.015660	0.009897*	0.012728
	SEMTRI	0.016277	0.011220	0.017158	0.010895*	0.018369
Morocco	CFG25	0.019533	0.012693	0.019919	0.010849*	0.018012
Namibia	LOCAL	0.007694	0.005547	0.005299	0.003355*	0.003611
	OVERALL	0.023320	0.025833	0.021608	0.018302*	0.041497
Tunisia	BVMT	0.013047	0.007897	0.012684	0.004640*	0.018007
	TUNINDEX	0.009716	0.007513	0.009778	0.006253*	0.008092
Zimbabwe	INDUSTRIAL	0.075491	0.055123	0.080064	0.040252*	0.076499
	MINING	0.104177	0.101397	0.104177	0.095418*	0.143216

* Indicates the lowest Theil's U coefficient and thus the model with the best/superior forecasting performance.
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

Theil's U inequality coefficients presented in Table 8.5 confirms the results above.[1] The U statistics for all the indices are relatively small (less than 10 percent) except for Zimbabwe's Mining index. However, even this index has a U statistic smaller than 10 percent under the EFAR model. Theil's U statistic confirms the superiority of the EFAR model in forecasting the indices.

While the GSE index significantly deviates from the RW and exhibits higher order serial correlation, it is the information in the immediate past that is important in

[1] The Theil Inequality coefficients are presented in a separate table because they are presented differently from the other forecast statistics.

predicting future index levels. For the GSE index, the AR outperforms all the models in forecasting future values. The poor performance of the EFAR model suggests that the return generating process for the GSE index is linear as opposed to nonlinear. Another interesting observation is that for the GSE index, the AR outperforms all the other alternative models quite significantly, with gains the highest over and above the GARCH (i.e. 285.78 percent).

8.6.1 Directional forecasts

The ability of a model to predict the correct directional change is of great interest to investors. This is because correctly predicting the direction impacts on the investor's decision to buy or sell a given stock. This is more so in markets with low transaction costs. In Table 8.6, the frequency (as a percentage) of correctly predicting the directional change of the indices is presented.

Table 8.6 shows that the RW model only correctly predicts directional change more than 50 percent of the time in only 3 indices, namely, Botswana's Domestic Companies Index (DCI), the GSE index and Mauritius' SEMTRI. The RW model, however, only gives the best performance in two indices, but outperforms all the alternative models in only one index. The AR and the EFAR outperform the RW in 12 and 11 indices, respectively, as compared to the ARMA and GARCH, which outperform the RW in only 4 and 6 cases, respectively. In more than one cases, the alternative models are just as good as the RW (chance). The EFAR model, although superior to the RW in correctly predicting directional change, is outperformed by the ARIMA for most indices.[2]

[2] The thinly traded Namibian Local Index was unchanged for the greater part of the forecast horizon, with the price only dropping once from 48 to 47. None of the models used successfully predicted this stagnation in the index. They all, however, predicted the index to be declining.

Table 8.6: Dynamic out-of-sample forecast performance: correct directional change Index

Country/ Exchange	Stock market Index	RW	AR	ARMA	EFAR	GARCH
Botswana	ACI	50.00	**52.50***	42.50	40.00	42.50
	DCI	52.50	**55.00**	52.50@	**60.00***	**55.00**
	FCI	37.50	**40.00***	27.50	25.00	**40.00***
BRVM	BRVM_10	47.50	**50.00***	42.50	**50.00***	42.50
	BRVM_C	50.00	50.00@	50.00@	50.00@	**55.00***
Egypt	EFGI	45.00	**72.50***	**50.00**	**72.50***	45.00@
	HFI	37.50	**75.00***	**42.50**	**65.00**	**45.00**
Ghana	GSE	82.50*	82.50*@	70.00	60.00	82.50*@
Mauritius	SEMDEX	37.50	**60.00***	32.50	**47.50**	**57.50**
	SEMTRI	67.50*	60.00	55.00	52.50	57.50
Morocco	CFG25	35.00	**57.50**	**42.50**	**62.50***	**55.00**
Namibia	LOCAL	2.50	2.50@	2.50@	2.50@	2.50@
	OVERALL	30.00	27.50	**45.00**	**40.00**	30.00@
Tunisia	BVMT	45.00	**55.00***	42.50	**55.00***	42.50
	TUNINDEX	47.50	**52.50***	45.00	**50.00**	42.50
Zimbabwe	INDUSTRIAL	40.00	**62.50***	40.00@	**60.00**	40.00@
	MINING	40.00	**42.50**	40.00@	**52.50***	40.00@
# of times model gives best performance		*2*	*10*	*1*	*6*	*3*
# of times greater than 50%		*3*	*11*	*3*	*9*	*6*
# of times equal to 50%		2	2	2	*3*	*0*
# of times model outperforms the RW		-	*12*	*4*	*11*	*6*
# of times model is as good as the RW		-	*3*	*5*	2	*6*

* Indicates superior performance
Bold indicates that the model outperforms the RW
@ indicates performance that is just as good as the RW
Source: Chipo Mlambo (2003), University of Stellenbosch Business School

8.7 Remarks and conclusion

The out-of-sample predictability of stock indices on selected African stock markets is investigated. This is done by comparing the forecasting performance of nonlinear to linear models and benchmarking with the RW model. The results are quite interesting. The RW was not outperformed by any of the alternative models in only two highly correlated indices, Botswana's FCI and ACI. The linear ARIMA models, collectively, gave the best forecasting performance in only four indices. The remaining 11 indices were forecast best with a model that is nonlinear in the conditional mean (the EFAR). The GARCH-in-mean model did not give the best performance in any of the indices, although it occasionally outperformed the RW. This could be interesting to emerging market researchers who recommend the GARCH family of models in testing the EMH, arguing that these models are robust enough to detect nonlinear predictability in stock prices. The results in this chapter also support the assertion that the null hypothesis of no predictability in emerging markets can be wrongly accepted with the serial correlation and runs tests if the return generating process is nonlinear.

The ability to correctly forecast directional change, although necessary, is not sufficient to trade profitably in markets where transaction costs are high. Therefore, although the AR model exhibit superiority in predicting correct directional change, the EFAR is much more superior in that, besides outperforming the RW in predicting correct directional changes, it also manages to predict the actual price levels with smaller errors for the majority of indices.

In this study, dynamic forecasting is used, whereby the sample size is continuously enlarged with the forecast values. However in real life, there is no reason why investors would not use new information as it becomes available. Therefore, it will be interesting to also investigate the performance of these models in one-step-ahead predictions, static forecasting. If the EFAR can still outperform the RW and other alternative models, then it can be a tool worth serious consideration for use in financial markets. The only challenge will be to find the optimal functional specification of the feedback function. While the transition functions for the STAR models are well established, the exponential feedback function used in this study for our EFAR model is only novel.

The stocks listed on the GSE and Stock Exchange of Mauritius were found to deviate from the RW in Mlambo and Biekpe (2003) using the serial correlation and runs tests. It is observed in this chapter that the GSE Index is forecast best with the linear AR model. For Mauritius, the AR performed relatively well, although the nonlinear EFAR model marginally outperformed it. While the efficiency or inefficiency results of some of the African markets studied in Mlambo and Biekpe (2003) were not conclusive, in this chapter, the findings suggest that there are some exploitable patterns in these markets' stock indices, which can be used to predict future values. Such patterns, however, appear nonlinearly and are thus more detectable using nonlinear modelling techniques.

8.8 A critique of the EFAR model vis-à-vis the STAR models

The EFAR model as it is specified in this study is simply a modification of the STAR models. STAR models have been used to model the transition of economic and financial time series data from one regime to the other. Their main aim is to forecast turning points of a business cycle. The data used in estimating the STAR models are growth rates. The EFAR, on the other hand, is used to model nonlinearities in stock returns rather than their growth rates. Its main aim is to predict future values of the variable, in this case, future stock prices.

In the specification of the STAR models by Sarantis (2001), the delay index was restricted to $1 \leq d \leq 6$. The EFAR also adopted this restriction. However, since d specifies the lag that causes nonlinearity in the time series, then significant autocorrelations for lags 1 to 30 should have all been considered, since autocorrelation was first investigated for this range.

Whilst it is hypothesized that over-parameterisation leads to poor forecasting performance in the case of ARIMA models, the hypothesis of which has been supported in this study, it is possible that the EFAR model as it is used here is also over-parameterised since it used as many explanatory variables as were used in the ARIMA model. Since the ARIMA model performed poorly, this could imply that the superior performance of the EFAR is due to the nonlinearity incorporated into the model. Since the AR model gave the best performance among the linear models, it is most likely the case that the EFAR that uses only one lagged explanatory variable could give a performance much more superior to the over-parameterised EFAR. Over-parameterisation also leads to a loss of degrees of freedom.

In deciding on the power of the feedback function, the rules used for the STAR models in choosing between two competing STAR models (logistic versus exponential)[3] were also adopted.

With the EFAR, however, these rules were used to decide on the power of the exponent, in order to uniquely define the pattern of feedback for each market index. However, these model selection rules, proposed by Teräsvirta and Anderson (1992), apply only to specific STAR models and are not readily generalised. The F-functions in the STAR models were chosen based on Taylor expansions. The argument was that the third order expansion of the logistic transition function contains the component R_{t-d}^3 but that of the exponential transition function does not, thus the use of a sequence of F tests to identify the correctly specified model. Therefore, direct application of these rules to the EFAR becomes questionable, considering the above arguments. Even in their application to STAR models, the rules have been criticised for the following reasons (Chen, 2003):

1. Competing STAR models are typically non-nested and thus can be evaluated using non-nested tests. Unfortunately, conventional non-nested tests either have poor finite sample performance or are difficult to implement;
2. The theoretical properties of the rules used are not completely known;
3. The bounded transition functions may not be well approximated by their Taylor expansions, which are unbounded. This problem is more severe when the data do not possess proper moments;
4. The rules are unable to distinguish between third-order Taylor expansions for the logistics function and the fourth-order expansion for the exponential function (when $c \neq 0$) because R_{t-d}^3 appear in both expansions.

The so-called feedback function for the EFAR is over-simplified in that it does not have any coefficients to be estimated. The pattern of the price reverting back to its intrinsic value could be much more complicated than that and specific for each

[3] The two competing functions are the logistic function: $F(R_{t-d}) = \frac{1}{1+\exp\{-\gamma(R_{t-d}-c)\}}$ and the exponential function is: $F(R_{t-d}) = 1-\exp\{-\gamma(R_{t-d}-c)^2\}$

market. In addition, whilst the model is based on the argument that the cause of the nonlinearity is due to the price reverting back to its intrinsic value, as it is hypothesised to do especially after an overreaction, the model can be significantly improved if it can be used to model other sources of nonlinearities. These include diversity in agents' beliefs, heterogeneity in investors' objectives arising from varying investment horizons and risk profiles, and herd behaviour, among others.

9 THE SMALL-FIRM AND PRICE-EARNINGS EFFECTS ON AFRICAN STOCK MARKETS

9.1 Introduction

The testing of market efficiency is considered a joint hypothesis problem in that both the asset-pricing model, usually the Capital Asset Pricing Model (CAPM), and the Efficient Market Hypothesis (EMH) are assumed to be correct. It involves testing whether a trading strategy beats the market on a risk-adjusted basis, whereby adjusting for risk requires an asset-pricing model. In this case, the failure of the EMH to hold may reflect a faulty asset-pricing model rather than indicate the inefficiency of the market.

According to the CAPM, or the Sharpe (1964), Lintner (1965) and Black (1972) (SLB) model, given simplifying assumptions, the rate of return on any security is linearly related to that security's systematic risk or beta measured relative to the market portfolio of all marketable securities. Such a relationship between average returns and beta has been documented as positive (e.g. Pettengill, *et al.,* 1995). Some studies in the 1970s (e.g. Black, *et al.,* 1972; Blume and Friend, 1973; Fama and MacBeth, 1973) found the estimated intercept to be higher than the risk-free rate and the estimated coefficient on beta to be much lower than predicted by the CAPM, and only marginally important in explaining cross-sectional differences in average security returns (Hawawini and Keim, 1995).

Due to the lack of support of the CAPM, alternative models have been formulated adding to the so-called market efficiency anomalies. Among these anomalies are the price-earnings and firm size effects of Basu (1977) and Banz (1981) respectively. Basu (1977) and Banz (1981) found that the ratio of price-to-earnings (P/E) and the market capitalisation of common equity (ME), respectively, provide considerably more explanatory power than beta.

This chapter extends the investigation of these two anomalies to some African stock markets. Although the periods investigated are relatively short, in comparison to similar studies on other markets, the study will serve as a reference point for future research on African markets. There is currently no published research, according to our knowledge, that tackles the same issues on African markets as tackled in this chapter, yet there is a constant need to keep up-to-date with research on other markets. Hawawini and Keim (1995) suggested that the analysis of international evidence on the size effect, where the market organizations and structures are very different, may be quite useful in understanding the cause of the size effect. These differences could be related to differences in the liquidity of markets (Reinganum, 1990).

9.2 Data and methodology

Data (stock prices, volume traded, ME, and P/E ratios) for Egypt, Morocco, Kenya and Zimbabwe was obtained from DataStream, whilst for Botswana, Tunisia and Namibia, data was obtained from the respective stock exchanges. The P/E data obtained from DataStream consist only positive values. The negative P/E values are probably excluded from the time series. Therefore, the analysis in this study is only based on the positive ratios.[1] Due to the problem of thin trading on African stock markets, beta is estimated using the trade-to-trade approach (Bowie, 1994; Bradfield and Barr, 1989; Dimson, 1979). Bowie (1994) found the trade-to-trade beta estimation method to be superior to other methods in correcting for thin trading in terms of both unbiasedness and efficiency. In addition, this approach is also the best in estimating betas of individual stocks. This means that in the analyses done in this study, there is no need to allocate portfolio betas to individual stocks as is the case in prior studies. Thus a unique beta is allocated to each stock.

The Fama and MacBeth (1973) regressions are only carried out on those markets where the sampled stocks are at least 30. These markets are Egypt with 55 stocks in the sample, Kenya with 40 stocks, Morocco with 36 stocks, Tunisia with 35 stocks and Zimbabwe with 39 stocks. These sample sizes are, however, small in comparison

[1] In some studies (e.g. Lau *et al.* (2002) and Lam (2002)), the negative P/E ratios have been represented by a dummy variable in the Fama-MacBeth regressions.

with those used in studies on other markets. For example, the sample size used by Fama and French (1992) was composed of, on average, 2267 stocks per month. Due to the small number of stocks for each market, portfolios are not created using deciles as is the case in some studies. Stocks are allocated into one of three portfolios, "SMALL, MEDIUM and LARGE" for size portfolios, "LOW, MEDIUM and HIGH" for P/E portfolios. No portfolios are formed based on beta since no pre-sampling betas are measured. The limiting factor is the data, which only covers a very short horizon, with the longest period covered being 5 years and 5 months, that is, from January 1997 to May 2002 for Egypt, Morocco, Kenya and Zimbabwe. However, since this is probably the first attempt, to examine the cross-sectional return predictability of the African stock markets herein, the importance of this research overrides these constraints.

One of the criteria used to include a stock in the sample is that the stock should have been listed for the entire period under consideration. This is argued to induce survivorship bias in the results. However, a study by Elfakhani and Wei (2003) assessed the presence and direct effect of survivorship bias on the Canadian markets by constructing three sample groups: the survivor group, which included stocks that survived until the end of the testing period; the delisted group; and the overall sample group. They found that although the delisted group returns were statistically different from those of the survivor and overall groups, indicating some evidence of survivorship bias, the difference between the survivor group and the overall group was weak. They concluded, therefore, that the survivorship problem might not be as severe as was originally hypothesised. This, however, may not be the case on African markets due to the significant number of stocks that delist every year. The survivorship bias could be serious and thus future research of this nature should make use of data that is free from this bias.

9.3 Size effect

Banz (1981) pioneered the research investigating the relation between stock returns and the market value of common equity. He found that market equity (ME) adds to the explanation of the cross-section of average returns provided by market betas, and in fact has more explanatory power than beta, a result that is contrary to earlier studies of the CAPM. The relationship between returns and size (ME) was found to be negative, suggesting that average returns on low ME stocks are high given their beta estimates and average returns on large stocks are low. Evidence from studies such as Hawawini and Keim (1995), Reinganum (1981) and Roll (1981) supported this finding. Reinganum (1981), using daily data for stocks drawn from the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) over the period 1963 to 1977, showed that portfolios of small firms have significantly higher average returns than large firms, with a size premium[2] of 30 percent annually. Hawawini and Keim (1995) found an annualised size premium for the same markets of about 7.9 percent for the period April 1951 to December 1989.

Other studies, however, failed to find clear size effects. For example, Horowitz, *et al.* (2000), using annual compound returns, monthly cross-sectional regressions, and linear spline regressions, investigated the relation between expected returns and firm size for NYSE, AMEX and NASDAQ stocks during 1980-1996. They reported no consistent relationship between size and realised returns and concluded that the widespread use of size in asset-pricing is unwarranted. Similarly, Elfakhani and Wei (2003) examined the relation between average returns, firm size and price levels for Canadian stocks during the 1975 to 1994 period. According to them, their evidence, in support of an independent size effect, was less clear. A small size effect existed only among the higher share price denominations.

Similar models to the one used by Banz (1981) for the US market have also been estimated for other markets. In most countries, market risk shows no explanatory power for stock returns, while a size effect is generally observed. Hawawini and Keim (1995) presented evidence from prior studies on countries other than the US showing the monthly size premium to be positive. Chui and Wei (1998) documented a size effect for Hong Kong, Korea, Malaysia and Thailand but not for Taiwan.

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[2] The size premium is the difference between the average monthly return on the portfolio of smallest stocks and the average monthly return on the portfolio of large firm stocks.

Lau, *et al.* (2002) examined the relationship between stock returns and beta, size, the earnings-to-price (E/P) ratio, the cash flow-to-price (C/P) ratio, the book-to-market (B/M) equity ratio and sales growth for Singapore and Malaysia for the period 1988-1996. They found a conditional relationship between beta and stock returns for both countries, and a negative relationship between stock returns and size (size effect).

Lam (2002) investigated the relation between stock returns and beta, size (ME), leverage, B/M equity ratio and the E/P ratio in the Hong Kong stock market for the period July 1980 to June 1997. He found that beta is unable to explain the average monthly returns for stocks continuously listed on the Hong Kong Stock Exchange for the period July 1984 to June 1997. Size, as well as B/M equity and E/P ratios seemed able to capture the cross-sectional variation in average monthly returns over the period.

Cavaliere and Costa (1999) investigated the relation between firm size and asset returns on the Italian Stock Exchange using a sample of 178 firms for the period 1986 to 1995. They found firm size to be an important component of the return-generating process in Italy and suggest that the size premium can be interpreted as a risk factor. The size effect was, however, unrelated to seasonal effects, in particular the January effect as has been found in some literature.

Elfakhani (2000) examined the relationship between short interest and subsequent stock returns, and whether that relationship is attributable to firm size. The results supported the notion that short sellers correctly predicted price movements for the period 1986 to 1990 on the US market. The results also showed that following the monthly report of short interests, investors can still earn higher returns on shorted stocks, especially the small ones. Short interest positions on less liquid overpriced small stocks were found to be more profitable than more liquid overpriced large stocks, in support of the liquidity hypothesis.

Pinfold, *et al.* found that investment strategies designed to exploit B/M and size effects on the New Zealand share market are less successful due to the small number of equities listed on the market and the high volatility in returns of individual equities.

The New Zealand market is small and illiquid by world standards. In the following sub-section, the size effect is also investigated for African stock markets. These markets are also characterised as small as illiquid, in comparison to stock markets elsewhere.

9.3.1 The size effect: empirical African evidence

Table 9.1 does not show any clear pattern of a negative relation between size and average return for all markets except Mauritius and Zimbabwe. For Mauritius, average returns are highest for the small-size portfolio (0.70 percent) and lowest and negative for the large-size portfolio (-0.14 percent) and thus a monthly size premium of 0.84 percent (or 10.08 percent annually). For Zimbabwe, average returns fall from 4.29 percent for the small-firm portfolio to 1.75 percent for the large-firm portfolio. This gives a monthly size premium as high as 2.54 percent (or 30.48 percent annually).

The positive relation between average returns and beta assumed by the Sharpe-Lintner-Black (SLB) model is not evident on the African markets in this study for the size-sorted portfolios. Beta is only highest for high-return portfolios for Morocco and Namibia. For Botswana, Egypt, Kenya and Mauritius, the highest beta is obtained for those portfolios that give the lowest returns, contrary to literature. There is no clear pattern for Tunisia and Zimbabwe, where the highest beta is obtained for medium-sized portfolios. Fama and French (1992) also inferred that controlling for size, there is no relation between beta and average return for the period 1963 to 1990 on the US markets.

The size effect is known to be associated with the January effect. Past evidence has shown that the size effect is most pronounced in the month of January, suggesting a common underlying factor. Chen and Jindra (2001) investigated seasonal variations and size-related differences in cross-stock valuation distribution. They found that the average valuation level is the highest in mid-summer and the lowest in mid-December. They also found that among the size groups, small-cap stocks exhibit the sharpest decline in valuation from June to December and the highest rise from December to January. For most months, small-cap stocks had the lowest valuation among all size groups. In a typical month, small-cap stocks showed the widest cross-stock valuation dispersion, meaning they are also the hardest to value.

Table 9.1: Monthly average returns and other characteristics for equally weighted portfolios formed on the basis of size (market capitalisation)

Stock market	Size-sorted Portfolios	Average Returns (%)	No. of Stocks	ME (mil. Local currency)	P/E ratios	Standard beta	Trade-to-trade beta
Botswana	Small	1.70833	4	51.08992	-	0.08468	0.13144
	Medium	2.16828	4	280.13231	-	-0.00719	0.05358
	Large	2.07917	4	1570.00304	-	0.06217	0.06392
Egypt	Small	-1.48686	18	33.79866	6.08957	0.38649	0.49076
	Medium	-1.12865	18	144.82805	10.37294	0.34087	0.33916
	Large	-1.67006	19	1225.60796	18.97144	0.60575	0.58636
Kenya	Small	-1.20353	13	208.79225	8.77217	0.33722	0.53508
	Medium	-1.06860	13	1057.64948	9.12102	1.01178	1.00085
	Large	-1.51533	14	6341.40614	14.24702	1.01096	1.03869
Mauritius	Small	0.70301	3	812.62500	5.96204	0.67161	0.65754
	Medium	0.33678	3	2529.58130	7.47469	0.94671	0.95059
	Large	-0.14795	3	5098.42037	9.05185	1.37249	1.38847
Morocco	Small	-0.14390	11	160.58138	52.20249	0.51068	0.68319
	Medium	-0.06099	12	1111.41344	25.89973	0.64833	0.74293
	Large	-0.04017	12	6908.46503	29.98346	1.03632	1.02529
Namibia	Small	-1.52625	5	12.93883	-	0.00229	0.01292
	Medium	-2.39963	6	258.69164	-	0.09673	0.64461
	Large	0.49657	6	10863.05094	-	0.55331	0.70343
Tunisia	Small	-0.28981	11	13.13075	19.24579	0.22996	0.21440
	Medium	0.32735	11	48.49088	13.18172	0.28578	0.27459
	Large	-0.12365	11	200.01306	12.86282	0.42953	0.46126
Zimbabwe	Small	4.28918	13	130.30565	7.63346	0.73819	0.85979
	Medium	3.22538	13	540.68894	7.99712	0.93345	0.93088
	Large	1.74794	13	6771.00055	1865.46007*	0.86895	0.86076

Portfolios are formed quarterly with the stocks sorted by the market capitalisation of the month preceding each quarter and their equal-weighted returns calculated for the next 3 months. The average return (in percent) is the time series average of the monthly equal-weighted portfolio returns. Beta is a time series average of the monthly portfolio betas. These portfolio betas are obtained by averaging the individual firm betas. We report both the standard betas and the trade-to-trade betas.

* The P/E ratios for this portfolio are very high due to the high P/E ratios for Ashanti, especially for the last 6 months of the series.

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

In Table 9.2, the size effect (exhibiting a small-firm premium) is specific to January only for Kenya and Morocco. The size effect for Zimbabwe is not specific to the month of January, although it is more pronounced in that month. In other countries, the size effect is found in months other than January. There is a size effect in May and December for Botswana, in February and July for Egypt, in May, June, August and September for Mauritius and in December for Tunisia. For Namibia, there is no visible size effect in any of the months.

Table 9.2: Average returns (%) for size-sorted portfolios by month of the year

Stock market	Size- sorted Portfolios	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Botswana	Small	-1.9881	2.9739	0.3158	5.7073	4.7035	-2.2367	5.1452	0.7030	0.9324	-0.2379	0.6144	2.1186
	Medium	1.0334	-3.2512	1.8045	2.2140	3.1839	7.9896	2.7724	4.1514	-1.2120	1.0458	4.5938	1.4285
	Large	1.3126	4.5897	10.2909	3.0474	-4.9099	0.1738	5.2089	12.6567	-8.1061	3.6976	0.2420	-1.7483
Egypt	Small	2.2941	4.8492	-5.9067	-0.5613	-4.9818	-7.4567	-4.3907	0.3234	0.0944	-1.8702	-1.4411	1.3359
	Medium	4.8049	-1.3873	-4.0455	-2.4144	-3.2511	-3.4385	-4.7010	1.7166	0.3625	-0.1172	-1.6554	1.8995
	Large	4.0208	-1.4048	-2.5991	-1.4504	-5.2679	-4.7217	-5.5967	0.0881	1.9651	-1.1646	-3.0132	-0.0880
Kenya	Small	4.6926	0.1746	-2.6746	-3.6968	-1.0319	-0.4338	-2.5511	-1.6976	-2.4692	-0.5723	-3.3439	-0.3554
	Medium	3.4125	-0.1364	-1.1367	-4.4150	0.0333	-1.4245	-1.1582	-5.1120	-1.9123	0.9906	-2.9130	1.2244
	Large	1.2381	0.4637	-7.7175	-1.8441	-1.0921	0.5524	-0.8415	-3.7618	-1.7864	-1.8903	-3.0167	2.3382
Mauritius	Small	3.2926	0.9277	-3.8405	-1.2530	0.4809	3.7416	0.2864	0.8322	-0.0111	0.9907	1.4275	1.3874
	Medium	2.1362	-1.4018	0.5825	-0.8811	-0.4743	3.5591	1.6394	-0.5237	-1.2134	-1.4632	0.2971	2.0845
	Large	2.5326	-1.3591	-1.2637	-2.6388	-0.8520	1.5448	2.0958	-1.0262	-3.3922	-0.4980	1.9892	0.8625
Morocco	Small	1.9880	-0.2846	0.9834	0.5968	-1.9378	-1.6454	0.0439	1.7905	-0.1854	-1.1007	-1.0890	-0.8730
	Medium	-0.9396	1.3507	1.2357	1.6200	-1.4934	-0.8914	-1.2875	2.7957	-1.2093	-2.5424	-1.5127	1.5509
	Large	-1.2872	2.8236	1.7458	0.4406	-1.6461	1.1786	-1.1246	3.9778	-2.3846	-2.8305	-0.2079	-1.8724
Namibia	Small	-2.9001	0.4393	-2.3460	-0.4600	2.2988	-1.7520	7.1728	-3.1705	0.6602	1.0944	-14.6985	-2.3772
	Medium	1.6968	-5.1861	-4.1677	-3.2174	-3.3165	3.1623	0.1716	-8.3371	-5.1244	-7.8712	2.5097	1.6163
	Large	0.0804	-0.9025	-2.7009	-1.8535	-0.9355	6.2932	0.4600	0.2383	-2.0740	-1.0890	3.2397	7.0366
Tunisia	Small	1.7014	-0.0690	-0.3616	-0.8522	0.1514	-2.8366	-0.3040	-0.9559	0.0416	-0.5010	-1.8871	2.7936
	Medium	0.5054	0.4290	-1.9591	-1.5153	0.9922	-0.6244	0.2290	0.0384	1.3311	2.5905	0.9380	1.0093
	Large	3.1934	2.5087	-1.0469	-0.9236	-0.6806	-2.7608	0.1654	1.3657	-0.6660	-1.3054	-0.9284	0.2581
Zimbabwe	Small	22.2239	2.5858	7.4982	3.2251	4.4970	5.7787	0.8798	-0.1523	1.7034	1.4792	2.9875	-1.3660
	Medium	21.2728	-0.5468	5.6380	0.0772	3.5448	5.4118	5.9706	-4.0006	-0.5085	3.0432	2.9396	-3.2998
	Large	12.2523	-2.8527	8.3309	-1.3327	3.0034	4.8720	3.2391	-4.5709	6.1596	-4.4910	-1.3652	-2.3010

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

Roll (1981) conjectured that the size effect could be attributed to a misspecification in the market model commonly used to estimate systematic risk. He proposed that since small firms were likely to be less frequently traded than large firms, a nontrading adjustment would suffice to explain the anomaly. Reinganum (1982), however, found that the effect still holds even after estimating betas using methods that account for nonsynchronous and infrequent trading.

Other theories that have tried to explain the small-firm effect include the 'neglected firm' and 'liquidity' effects. The neglected firm effect suggests that small firms are less researched and thus they suffer from an information deficiency making them riskier investments and thus higher returns. The 'liquidity' effect, on the other hand, suggest that investors demand a rate of return premium in order to invest in less liquid stocks that entail higher trading costs. The literature also suggests that the size effect is related to some seasonal effects, and most importantly the January effect.

Size (ME) has also been considered a proxy for stock risk. Some evidence suggest that size produces a wide spread of average returns and betas. The problem is, however, that size and the betas of size portfolios are highly correlated (-0.988 in Chan and Chen, 1988) so asset-pricing tests lack power to separate size from beta effects in average returns (Fama and French, 1992).

Other possible explanations suggested for the existence of the small-firm effect include data mining, macroeconomic risk factors, tax-loss selling, liquidity effects, transaction costs, share price level, neglected firm effect and the differential information effect (see Elfakhani and Wei, 2003).

9.4 P/E effect

One inconsistency to the EMH that the value strategy tries to exploit is the P/E anomaly. This anomaly says that portfolios of low P/E ratios have higher returns than do the high P/E portfolios. This could be explained by the fact that if 2 stocks have the same expected earnings, then the riskier stock will sell at a lower price and thus the lower P/E ratio. Because of its higher risk, the low P/E ratio stock will have higher expected returns. Graham and Dodd (1940), according to Hawawini and Keim (1995), advocated that a prudent investor should never pay as much as 20 times earnings and a suitable multiplier should be 12 or less.

The first extensive study on the relation between P/E multiples and subsequent total returns was provided by Nicholson (1960). The evidence suggests that low P/E stocks consistently provide returns greater than the average stock. Basu (1977) introduced the notion that the P/E ratios may explain violations of the CAPM and found that for his sample of NYSE firms, there was a significant negative relation between P/E ratios and average returns in excess of those predicted by the CAPM. Basu (1983) showed that P/E ratios help explain the cross-section of average returns on US stocks in tests that also include size and beta. Ball (1978) argued that the P/E ratio is a catchall proxy for unnamed factors in expected returns. The P/E ratio is, therefore, expected to explain the portion of expected returns that is in fact compensation for risk variables omitted from the tests.

Aggarwal, *et al.* (1988) provided evidence of a significant P/E effect for a sample of 574 firms listed on the first section of the Tokyo Stock Exchange for the period 1974 to 1983. Portfolios of low P/E stocks outperformed those with relatively higher P/E stocks even after controlling for differences in systematic risk and size across portfolios. Levis (1989) documented the presence of a significant P/E effect on the London Stock Exchange over the period April 1961 to March 1985. He reported an average monthly premium of 0.58 percent. However some studies suggest otherwise. For example, Gillan (1990) found evidence that portfolios based on low P/E ratios do not earn significantly higher risk-adjusted returns than portfolios based on high P/E ratios on the New Zealand Stock Exchange for the 1977 to 1984 period. Kim, *et al.* (1992), reached a similar conclusion, finding neither a size effect nor a P/E effect on the Korean Stock Exchange for the period 1980 to 1988 for a sample of up to 224 stocks.

Chou and Johnson (1990) reported a significant P/E effect for the Taiwan stock Exchange during the period 1979 to 1988 for a comprehensive sample of shares with positive earnings. They found that the average monthly return of the lowest quintile P/E portfolio exceeds that of the highest quintile P/E portfolio by 2.27 percent. Chou and Johnson (1990) found that after adjusting for differences in systematic risk, the P/E premium is still significant with an average monthly return of 1.88 percent. Ma and Shaw (1990) reported a weaker but still significant P/E effect for a smaller sample of stocks over the period 1979 to 1986. Dividing their sample into 5 portfolios, they found a significant average risk-adjusted monthly P/E premium of 0.85 percent.

Banz and Breen (1986) found a size effect but no independent P/E effect. Using data for the period 1975-1985, Wong and Lye (1990) found that in Singapore stock returns are related to both firm size and P/E, but that the size effect is of secondary importance.

Park and Lee (2003) investigated which valuation model, using P/E ratio, price-book value (P/B) ratio, price-sales ratio and price-cash flow ratio, is the best in forecasting stock prices, and in identifying portfolios which generate higher returns. They found the P/B ratio the best, in terms of prediction accuracy, while results vary across the industry in portfolio selection.

9.4.1 P/E effect – empirical African evidence

In the literature, the inverse of the P/E ratio, the E/P ratio, is sometimes used in investigating the role of P/E ratios in explaining average stock returns. While with the E/P, the hypothesis is that of a positive relation between E/P and average return, with the P/E ratio, a portfolio of low P/E stocks is expected to give higher returns than the other portfolios. This relation of low P/E ratio stocks giving high average returns, hypothesised in the literature for some developed markets, is also evident for some African markets (see Table 9.3).

Table 9.3: Monthly average returns and other characteristics for equally weighted portfolios formed on the basis of price-earnings ratios

Stock market	P/E-sorted portfolio	Average Returns (%)	Number of stocks	P/E ratios	ME (mil. Local currency)	Standard Beta	Trade-to-trade Beta
Egypt	Low	-1.39625	15	4.14780	107.24145	0.42942	0.47742
	Medium	-1.56587	16	7.90272	445.47530	0.48399	0.47955
	High	-2.09158	16	24.46597	1030.19617	0.53273	0.53390
Kenya	Low	-0.52245	11	4.36725	1793.09674	0.78207	0.88756
	Medium	-1.15079	11	7.29587	2994.18237	0.69507	0.79089
	High	-1.51553	12	20.40053	3717.48951	0.77491	0.83251
Mauritius	Low	0.39446	3	4.22932	1725.44994	0.74747	0.75498
	Medium	0.18046	3	7.25247	3571.21435	1.02383	1.03497
	High	0.39795	3	11.17037	3803.50611	1.23667	1.23258
Morocco	Low	0.22926	10	11.20220	1845.59381	0.74377	0.82471
	Medium	-0.09479	10	18.58739	3670.98013	0.78271	0.80663
	High	-0.24565	11	70.98956	3583.13845	0.73479	0.81199
Tunisia	Low	-0.45301	10	7.93320	84.68352	0.31352	0.31801
	Medium	-0.41043	10	10.54709	98.20028	0.25869	0.24491
	High	-0.35635	11	24.09901	106.56017	0.39665	0.37525
Zimbabwe	Low	2.49599	11	3.21554	444.94813	0.88272	0.92966
	Medium	3.05050	11	6.67285	1136.51462	0.91083	0.96079
	High	3.37475	12	1609.99768	5764.60969	0.81844	0.80973

Portfolios are formed quarterly with the stocks sorted by the PE ratios of the month preceding each quarter.
Source: Chipo Mlambo (2004), University of Stellenbosch Business School

For Egypt and Kenya, although average returns are negative for all stocks, the losses on the low P/E ratio portfolios are the lowest, while they are the highest for the high P/E ratio portfolios. For Morocco, the low P/E portfolio gives a positive return of 0.23 percent and a negative return on the high P/E portfolio, which is higher than that on the medium P/E portfolio.

While there is no clear pattern for Mauritius, a reversed low P/E ratio-high average return relation is observed for Tunisia and Zimbabwe. For Tunisia, while all average returns are negative, implying, on average, a loss on each portfolio, the loss is highest for the low P/E portfolio and lowest for the high P/E. For P/E-sorted portfolios, there is no clear pattern between average returns and beta for all the markets except Egypt. However, for Egypt, it is the high P/E portfolio with the lowest returns that gives the highest beta, implying a negative relation between average returns and beta.

Jaffe, *et al.* (1989a) found the P/E effect, unlike the size effect, to be significant throughout the year. However, they found that after controlling for size, the P/E effect will no longer be significant in January and the other months. An investigation was carried out to determine if the P/E effect is specific or most pronounced in January.

Table 9.4: Average returns (%) of P/E-sorted portfolios by month of the year

Stock Market	P/E- sorted portfolios	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Egypt	Low	4.3081	3.6022	-7.2689	-4.3699	-5.6038	-5.2634	-4.3203	3.3795	0.2853	-1.1973	-0.6786	1.9832
	Medium	3.3825	-1.8925	-2.3652	0.4885	-4.6302	-3.5053	-5.3353	-0.6828	0.4369	-2.2054	-2.1051	0.0506
	High	3.3964	-1.3677	-5.8469	-1.4411	-4.7039	-6.4980	-5.4594	0.9778	0.5504	-1.3808	-2.2681	-0.0590
Kenya	Low	4.6544	0.3371	-3.5841	-4.1370	3.7529	-0.0492	1.0360	-3.2642	-3.3445	0.1663	-1.4790	-0.0498
	Medium	2.9157	-0.2065	-5.0812	-2.3511	2.1079	-1.5342	-2.1824	-3.7012	-1.7858	-0.0527	-2.9997	1.2472
	High	3.0005	1.3764	-3.2145	-3.0446	-4.7393	1.3242	-1.2796	-1.9072	-1.0794	-3.7007	-5.8072	1.5969
Mauritius	Low	4.0862	-0.9291	-2.0510	-1.4061	-1.1129	4.9925	1.2871	0.0813	-0.3868	-0.7582	0.6534	0.5198
	Medium	2.7400	-0.8333	-1.7519	-2.9630	1.7080	2.6084	1.9259	-0.7496	-3.0466	0.8568	0.6283	1.1276
	High	1.9547	-0.2457	0.7568	-0.6500	-1.2483	2.2227	1.1827	-1.1869	-1.7010	-0.7276	1.2986	3.1998
Morocco	Low	-0.0757	1.3322	0.9120	0.9231	-1.4154	1.6343	-0.4079	4.0354	-0.7624	-1.4653	-1.4776	-0.6485
	Medium	0.1465	2.1309	1.0857	0.8174	-1.3409	0.8286	-0.6415	1.9758	-1.8579	-3.1638	-0.9221	-0.8106
	High	-0.5261	1.2520	1.5228	1.0127	-1.9703	-1.8665	-2.0377	3.2644	-1.5550	-2.5319	-0.2501	0.1778
Tunisia	Low	1.8801	-3.2002	-1.7607	-1.0117	1.7107	-2.1653	-0.7875	-1.0049	-0.3394	-0.6490	0.5456	0.6467
	Medium	0.2771	-2.6839	0.0993	0.0863	-0.0991	-3.0602	-0.8314	-0.4831	-0.0846	-1.1759	1.2122	0.8553
	High	3.1895	-2.7778	-2.4254	-2.8440	1.7118	-3.2858	2.8582	-1.7836	0.0828	-0.4810	-2.4708	3.4020
Zimbabwe	Low	22.0842	-1.7963	4.5884	0.3771	5.1209	4.7431	1.4350	3.2447	-4.1495	-2.2450	-1.1508	-1.9612
	Medium	19.3070	1.9313	8.3035	2.7454	2.9009	4.5287	5.0161	-10.1050	0.7241	1.6319	3.1735	-4.2871
	High	15.5021	-3.1296	7.8482	-0.4425	5.2545	5.4596	4.9486	-3.2888	7.8026	-0.1823	3.0718	-1.5538

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

The results of this investigation are presented in Table 9.4. The results show a P/E effect in January for Mauritius and Zimbabwe. While for Zimbabwe, the P/E effect is specific to January, for Mauritius, the effect is also evident in June. None of the remaining months exhibits a P/E effect in January. Egypt exhibits a P/E effect in December, Kenya in May and October, Morocco in June and July, and Tunisia in June.

Ramcharran (2002) examined the determinants of the P/E ratio of emerging equity markets by evaluating the importance of economic growth and credit risk as determinants of the P/E ratio of 21 emerging markets using annual data for the period 1992-1999. The multivariate results indicated the significance of growth and the univariate results, the significance of both growth and credit risk. He took his findings to be supportive of growth (earnings potential) as a determinant of cross-country variation of the P/E ratios in emerging markets.

Some studies looked at other stock valuation variables, other than size and the P/E ratios. Lewellen (1999), for example, examined the time-series relations between expected return, risk and book-to-market (B/M) at the portfolio level. He found that B/M predicts economically and statistically significant time-variation in expected stock returns. Dunne (1999) used the MGARCH-m model whose mean equation was designed to determine whether proxy sources of time-varying non-diversifiable risk could explain movements in excess returns on various types of portfolios. He found time-variation in conditional excess return to have a significant relation with time-varying conditional variance associated with a B/M factor.

9.5 Cross-sectional regressions

In Table 9.5, results of the month-by-month regressions are presented. The table shows that none of the average slopes are significantly different from zero. However, almost all the slopes are positive for size and the P/E ratio, contrary to the expected negative slopes. This shows that reversed size and P/E effects are present on these markets although they are not significant. The results support those given in Tables

9.1 and 9.3 where the large-stock and the high-P/E portfolios, respectively, give the highest returns. For beta, 12 out of 20 slopes are negative. This also is in support of results given in Tables 9.1 and 9.3 where high betas seem not to be associated with high returns.

Table 9.5: Month-by-month regressions of stock returns on beta, firm size and price-earning ratios

Stock market	Regr. Eqn.	Intercept			Trade-to-trade Beta			Ln(ME)			P(+)/E		
		coeff.	Std. Err.	t-stat	coeff.	Std. Err.	t-stat	coeff.	Std. Err.	t-stat	coeff.	Std. Err.	t-stat
Egypt	1	-0.0022	0.0543	-0.0403	-0.0256	0.1276	-0.2007						
	2	-0.0337	0.1091	-0.3089				0.0042	0.0171	0.2429			
	3	-0.0277	0.0610	-0.4533							0.0018	0.0036	0.5091
	4	-0.0230	0.0966	-0.2380	-0.0301	0.1328	-0.2268	0.0049	0.0186	0.2645			
	5	-0.0134	0.0539	-0.2492	-0.0275	0.1286	-0.2136				0.0017	0.0035	0.4983
	6	-0.0415	0.1349	-0.3075				0.0037	0.0235	0.1570	0.0011	0.0040	0.2687
	7	-0.0290	0.1096	-0.2646	-0.0294	0.1306	-0.2254	0.0043	0.0240	0.1805	0.0009	0.0041	0.2188
Kenya	1	-0.0064	0.0482	-0.1330	-0.0073	0.0651	-0.1117						
	2	-0.0326	0.0967	-0.3376				0.0030	0.0138	0.2155			
	3	-0.0145	0.0469	-0.3095							0.0002	0.0033	0.0747
	4	-0.0285	0.0956	-0.2979	-0.0122	0.0672	-0.1811	0.0040	0.0140	0.2827			
	5	-0.0143	0.0606	-0.2362	0.0006	0.0563	0.0111				0.0001	0.0035	0.0414
	6	-0.0313	0.0990	-0.3156				0.0027	0.0141	0.1901	0.0001	0.0036	0.0212
	7	-0.0284	0.0991	-0.2863	-0.0053	0.0575	-0.0922	0.0031	0.0139	0.2236	-0.0001	0.0037	-0.0320
Morocco	1	-0.0041	0.0343	-0.1198	0.0038	0.0608	0.0627						
	2	-0.0083	0.0627	-0.1318				0.0011	0.0099	0.1128			
	3	-0.0069	0.0468	-0.1484							0.0004	0.0020	0.2026
	4	-0.0083	0.0648	-0.1277	0.0022	0.0614	0.0353	0.0009	0.0098	0.0880			
	5	-0.0081	0.0524	-0.1549	0.0017	0.0624	0.0266				0.0004	0.0021	0.1834
	6	-0.0119	0.0743	-0.1605				0.0007	0.0107	0.0687	0.0004	0.0021	0.1882
	7	-0.0102	0.0766	-0.1336	-0.0018	0.0618	-0.0294	0.0007	0.0115	0.0632	0.0004	0.0023	0.1644
Tunisia	1	-0.0027	0.0270	-0.0987	0.0082	0.0779	0.1048						
	2	-0.0124	0.0582	-0.2132				0.0032	0.0147	0.2162			
	3	-0.0060	0.0259	-0.2308							0.0002	0.0016	0.1193
	4	-0.0116	0.0586	-0.1976	0.0037	0.0818	0.0452	0.0027	0.0147	0.1865			
	5	-0.0023	0.0224	-0.1024	-0.0006	0.0864	-0.0072				0.0000	0.0015	-0.0140
	6	-0.0175	0.0618	-0.2824				0.0027	0.0143	0.1856	0.0002	0.0016	0.1502
	7	-0.0157	0.0667	-0.2357	-0.0079	0.0955	-0.0822	0.0038	0.0163	0.2342	0.0000	0.0015	0.0307
Zimbabwe	1	0.0382	0.1305	0.2929	-0.0083	0.1906	-0.0437						
	2	0.0000	0.1983	-0.0002				0.0054	0.0259	0.2086			
	3	0.0052	0.1302	0.0396							0.0038	0.0048	0.7791
	4	0.0054	0.2066	0.0262	-0.0066	0.1908	-0.0347	0.0055	0.0260	0.2102			
	5	-0.0085	0.1471	-0.0576	0.0143	0.2116	0.0676				0.0038	0.0047	0.7982
	6	0.0087	0.2204	0.0395				0.0002	0.0288	0.0064	0.0034	0.0063	0.5434
	7	-0.0016	0.2154	-0.0075	0.0155	0.2170	0.0714	-0.0003	0.0294	-0.0099	0.0034	0.0060	0.5607

The coefficients are time-series averages of the monthly regression slopes for the periods investigated. Also reported in the table are the time-series standard errors and t-statistics of the average slopes, whereby the t-statistic is calculated as the average slope divided by its time series standard error. The regression equations estimated are as follows:

1. $R_{it} = \alpha_0 + \alpha_1 \beta_{it} + \varepsilon_{it}$
2. $R_{it} = \alpha_0 + \alpha_1 ME_{it} + \varepsilon_{it}$
3. $R_{it} = \alpha_0 + \alpha_1 P/E_{it} + \varepsilon_{it}$
4. $R_{it} = \alpha_0 + \alpha_1 \beta_{it} + \alpha_2 ME_{it} + \varepsilon_{it}$
5. $R_{it} = \alpha_0 + \alpha_1 \beta_{it} + \alpha_2 P/E_{it} + \varepsilon_{it}$
6. $R_{it} = \alpha_0 + \alpha_1 ME_{it} + \alpha_2 P/E_{it} + \varepsilon_{it}$
7. $R_{it} = \alpha_0 + \alpha_1 \beta_{it} + \alpha_2 ME_{it} + \alpha_3 P/E_{it} + \varepsilon_{it}$

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

Cross-sectional regressions are also done for the entire period, rather than month-by-month, the results of which are presented in Table 9.6. In all the markets, size alone does not help explain the cross-section of average stock returns. In addition, the slopes on size alone are all positive (although not significant), contrary to the negative size-average return relation observed in the literature for other markets (e.g. Banz, 1981). The insignificance of size as an explanatory variable for average stock returns persists even with other explanatory variables being included in the regressions for Morocco, Tunisia and Zimbabwe. However, for these markets, an insignificant negative relation is observed when size is combined with average price, both average price and beta, P/E ratio and price, P/E, beta and price as explanatory variables for Morocco; P/E ratio, beta and price for Tunisia; and with P/E ratio, average price, both beta and average price, P/E ratio, P/E ratio and average price, P/E, beta and average price for Zimbabwe.

The only significant relations between size and average returns are positive (contrary to literature) and are observed for Egypt and Kenya. For Egypt, this significant relation is observed when size is used in combination with (1) beta, (2) with price, and (3) with both beta and average price, while for Kenya this significant relation is obtained when size is used in combination with (1) beta, and (2) beta and P/E ratios. The regression results are in support of a reversed size effect on the African markets, contrary to results for other markets.

While for Morocco, Tunisia and Zimbabwe, beta shows no explanatory power for average returns, it has significant explanatory power in the regressions for Egypt and Kenya. Contrary to the expected positive relationship between expected returns and beta suggested in the Sharpe-Lintner-Black or CAPM model, the relation observed is a negative one for both Egypt and Kenya when beta is used alone and when used with other explanatory variables. While Fama and French (1992) report that beta shows no power to explain average returns in the Fama-MacBeth regressions, they however observed a positive (although insignificant) relation. Fama and French (1992) suggest that the poor results for beta could be (1) that other explanatory variables are correlated with true betas, which obscures the relation between average returns and measured betas. However, this possible explanation was discarded on the grounds that beta still has no power when used alone to explain average returns and the cross-sectional correlations between beta and these other variables were quite low. (2) Another suggested explanation was that the relation between beta and average returns is obscured by noise in the beta estimates (beta-measurement error). The evidence in Fama and French (1992), however, could not support this explanation.

Table 9.6: Cross-sectional return predictability: regression results

Country	Regr. Eqn.	Intercept	Beta[a]	Size	P/E Ratio	Average Price	R^2	Adj. R^2	F-stat
EGYPT	1	-0.0022 (-0.5687)	-0.0256 (-3.7735)***				0.2118	0.1969	14.2395***
	2	-0.0193 (-2.3743)**		0.0010 (0.6366)			0.0076	-0.0111	0.4053
	3	-0.0269 (-4.0556)***			0.0058 (2.0444)**		0.0757	0.0576	4.1797**
	4	-0.0021 (-0.2545)				-0.0036 (-1.5622)	0.0440	0.0260	2.4403
	5	-0.0128 (-1.7609)*	-0.0284 (-4.1409)***	0.0024 (1.7088)*			0.2537	0.2250	8.8377***
	6	-0.0136 (-2.0280)**	-0.0259 (-3.9825)***		0.0055 (2.1956)**		0.2983	0.2703	10.6289***
	7	0.0040 (0.5244)	-0.0242 (-3.4838)***			-0.0020 (-0.9391)	0.2249	0.1951	7.5449***
	8	-0.0238 (-2.7049)***		-0.0010 (-0.5399)	0.0067 (2.0224)**		0.0811	0.0443	2.2065
	9	-0.0092 (-1.0269)		0.0031 (1.7796)*		-0.0062 (-2.2955)**	0.0989	0.0642	2.8535*
	10	-0.0120 (-1.3250)			0.0073 (2.5977)**	-0.0053 (-2.2940)**	0.1638	0.1303	4.8956**
	11	-0.0152 (-1.8919)*	-0.0265 (-3.9179)***	0.0006 (0.3713)	0.0049 (1.6567)		0.3003	0.2575	7.0097***
	12	-0.0047 (-0.5878)	-0.0270 (-4.0436)***	0.0041 (2.6328)**		-0.0052 (-2.1867)**	0.3177	0.2775	7.9141***
	13	-0.0039 (-0.4687)	-0.0237 (-3.6603)***		0.0066 (2.6193)**	-0.0039 (-1.8322)*	0.3433	0.3031	8.5390***
	14	-0.0135 (-1.4069)		0.0010 (0.5071)	0.0065 (2.0428)**	-0.0059 (-2.2640)**	0.1681	0.1172	3.3010**
	15	-0.0067(-0.7803)	-0.0252 (-3.8570)***	0.0023 (1.2786)	0.0048 (1.6931)*	-0.0051 (-2.2106)**	0.3649	0.3120	6.8960***
KENYA	1	-0.0064 (-1.8284)*	-0.0073 (-2.1121)**				0.1051	0.0815	4.4609**
	2	-0.0224 (-2.3953)**		0.0014 (1.0589)			0.0287	0.0031	1.1213
	3	-0.0089 (-1.3381)			-0.0017 (-0.5925)		0.0092	-0.0169	0.3510
	4	-0.0320 (-3.7319)***				0.0057 (2.3045)**	0.1226	0.0995	5.3107**
	5	-0.0231 (-2.6918)**	-0.0100 (-2.8288)***	0.0028 (2.1125)**			0.2014	0.1582	4.6651**
	6	-0.0008 (-0.1033)	-0.0076 (-2.1938)**		-0.0024 (-0.8750)		0.1232	0.0758	2.5995*
	7	-0.0276 (-3.4077)***	-0.0086 (-2.6907)**			0.0067 (2.8504)***	0.2662	0.2265	6.7112***
	8	-0.0185 (-1.7069)*		0.0015 (1.1193)	-0.0020 (-0.7068)		0.0416	-0.0102	0.8030
	9	-0.0320 (-3.1336)***		0.0000 (0.0081)		0.0057 (1.9905)*	0.1226	0.0752	2.5855*
	10	-0.0273 (-2.7684)***			-0.0026 (-0.9686)	0.0061 (2.4175)**	0.1443	0.0981	3.1201*
	11	-0.0168 (-1.7058)*	-0.0108 (-3.0274)***	0.0030 (2.3065)**	-0.0033 (-1.2788)		0.2361	0.1724	3.7086**
	12	-0.0322 (-3.4500)***	-0.0098 (-2.8681)***	0.0014 (0.9943)		0.0054 (2.0629)**	0.2858	0.2263	4.8023***
	13	-0.0207 (-2.2401)**	-0.0092 (-2.9109)***		-0.0036 (-1.4624)	0.0072 (3.0936)***	0.3073	0.2496	5.3246***
	14	-0.0275 (-2.4434)**		0.0001 (0.0460)	-0.0026 (-0.9566)	0.0060 (2.0794)**	0.1444	0.0731	2.0247
	15	-0.0255 (-2.5280)**	-0.0106 (-3.1457)***	0.0016 (1.1592)	-0.0039 (-1.5727)	0.0059 (2.2545)**	0.3330	0.2567	4.3675***
MOROCCO	1	-0.0041 (-0.6969)	0.0038 (0.5678)				0.0103	-0.0216	0.3224
	2	-0.0061 (-0.6385)		0.0008 (0.5717)			0.0098	-0.0202	0.3268
	3	0.0095 (0.9545)			-0.0030 (-0.9881)		0.0296	-0.0007	0.9763
	4	-0.0341 (-1.8526)*				0.0053 (1.8223)*	0.0890	0.0622	3.3209*
	5	-0.0055 (-0.5142)	0.0033 (0.4145)	0.0003 (0.1563)			0.0112	-0.0570	0.1643
	6	0.0083 (0.6894)	0.0025 (0.3672)		-0.0034 (-1.0113)		0.0397	-0.0289	0.5781
	7	-0.0364 (-1.7402)*	-0.0030 (-0.3826)			0.0061 (1.6056)	0.0886	0.0279	1.4584
	8	0.0068 (0.5380)		0.0005 (0.3564)	-0.0032 (-1.0219)		0.0336	-0.0288	0.5384
	9	-0.0371 (-1.9233)*		-0.0012 (-0.7110)		0.0071 (1.8292)*	0.1035	0.0475	1.8479
	10	-0.0161 (-0.7627)			-0.0034 (-1.1130)	0.0043 (1.3725)	0.0852	0.0262	1.4435
	11	0.0081 (0.5714)	0.0024 (0.3073)	0.0000 (0.0275)	-0.0034 (-0.9812)		0.0397	-0.0670	0.3719
	12	-0.0381 (-1.7633)*	-0.0018 (-0.2227)	-0.0015 (-0.7259)		0.0078 (1.7208)*	0.1058	0.0100	1.1039
	13	-0.0171 (-0.7143)	-0.0027 (-0.3434)		-0.0037 (-1.1165)	0.0049 (1.2242)	0.0902	-0.0109	0.8918
	14	-0.0191 (-0.8704)		-0.0010 (-0.5884)	-0.0031 (-0.9950)	0.0057 (1.4349)	0.0956	0.0052	1.0575

	15	-0.0191 (-0.7814)	-0.0017 (-0.2052)	-0.0012 (-0.6144)	-0.0033 (-0.9863)	0.0062 (1.3568)	0.1032	-0.0348	0.7478
TUNISIA	1	-0.0027 (-1.1952)	0.0082 (1.6624)				0.0795	0.0507	2.7637
	2	-0.0096 (-1.6095)		0.0025 (1.6586)			0.0815	0.0519	2.7511
	3	-0.0044 (-0.4988)			0.0020 (0.6005)		0.0119	-0.0211	0.3607
	4	-0.0190 (-2.9345)***				0.0065 (2.9699)***	0.2109	0.1870	8.8202***
	5	-0.0093 (-1.5069)	0.0058 (0.9848)	0.0019 (1.1472)			0.1157	0.0547	1.8972
	6	-0.0046 (-0.5191)	0.0077 (1.5927)		0.0012 (0.3520)		0.0936	0.0289	1.4464
	7	-0.0196 (-2.9893)***	0.0061 (1.3405)			0.0061 (2.7174)**	0.2566	0.2086	5.3497**
	8	-0.0123 (-0.9575)		0.0017 (1.0542)	0.0025 (0.6709)		0.0448	-0.0234	0.6573
	9	-0.0223 (-2.9038)***		0.0012 (0.8126)		0.0060 (2.3955)**	0.2290	0.1776	4.4550**
	10	-0.0224 (-2.2318)**			0.0019 (0.6411)	0.0063 (2.8802)***	0.2317	0.1787	4.3721**
	11	-0.0091 (-0.6840)	0.0067 (1.1770)	0.0009 (0.4665)	0.0018 (0.4519)		0.0948	-0.0096	0.9078
	12	-0.0220 (-2.8450)***	0.0068 (1.2518)	0.0003 (0.1825)		0.0064 (2.4340)**	0.2701	0.1919	3.4544**
	13	-0.0224 (-2.1795)**	0.0064 (1.4579)		0.0014 (0.4645)	0.0060 (2.7386)**	0.2907	0.2119	3.6881**
	14	-0.0246 (-1.9332)*		0.0005 (0.3454)	0.0023 (0.6493)	0.0060 (2.5432)**	0.2294	0.1438	2.6797*
	15	-0.0219 (-1.7008)	0.0077 (1.4982)	-0.0007 (-0.3999)	0.0017 (0.4684)	0.0064 (2.6606)**	0.2946	0.1817	2.6098*
ZIMBABWE	1	0.0382 (3.9319)***	-0.0083 (-0.7928)				0.0167	-0.0099	0.6286
	2	0.0251 (2.1272)**		0.0009 (0.5070)			0.0069	-0.0199	0.2571
	3	0.0271 (5.9438)***			0.0018 (1.0655)		0.0298	0.0035	1.1352
	4	0.0234 (4.5940)***				0.0040 (1.7607)*	0.0773	0.0524	3.1002*
	5	0.0324 (2.1464)**	-0.0083 (-0.7846)	0.0009 (0.5040)			0.0236	-0.0307	0.4350
	6	0.0315 (2.4267)**	-0.0043 (-0.3618)		0.0015 (0.7857)		0.0333	-0.0204	0.6197
	7	0.0262 (2.1310)**	-0.0027 (-0.2479)			0.0038 (1.5589)	0.0789	0.0277	1.5415
	8	0.0275 (2.2724)**		-0.0001 (-0.0346)	0.0018 (0.9218)		0.0298	-0.0241	0.5529
	9	0.0296 (2.5183)**		-0.0012 (-0.5850)		0.0049 (1.7651)*	0.0860	0.0352	1.6936
	10	0.0228 (4.1671)***			0.0007 (0.3625)	0.0036 (1.4118)	0.0807	0.0296	1.5794
	11	0.0309 (2.0002)*	-0.0045 (-0.3624)	0.0002 (0.0724)	0.0014 (0.5967)		0.0334	-0.0494	0.4035
	12	0.0305 (2.0534)**	-0.0012 (-0.1078)	-0.0012 (-0.5331)		0.0048 (1.5499)	0.0863	0.0080	1.1020
	13	0.0244 (1.7562)*	-0.0015 (-0.1276)		0.0006 (0.2903)	0.0035 (1.3495)	0.0811	0.0023	1.0296
	14	0.0309 (2.5634)**		-0.0017 (-0.7565)	0.0012 (0.6050)	0.0045 (1.5939)	0.0955	0.0179	1.2312
	15	0.0290 (1.9053)*	0.0027 (0.2057)	-0.0020 -0.7635)	0.0014 (0.6220)	0.0048 (1.5417)	0.0966	-0.0097	0.9087

Cross-sectional regressions of average individual stock returns on a combination of independent variables consisting of beta, size (market capitalisation), price-earning ratios and average prices. All the independent variables, except beta, are in natural logarithms.

* Significance at the 10% level

** Significance at the 5% level

*** Significance at the 1% level

[a] Beta obtained using the trade-to-trade approach for individual stocks

Figures in parenthesis are t-statistics

The equations estimated are as follows:

1. $R_{it} = \alpha_0 + \alpha_1\beta_{it} + \varepsilon_{it}$
2. $R_{it} = \alpha_0 + \alpha_1 ME_{it} + \varepsilon_{it}$
3. $R_{it} = \alpha_0 + \alpha_1 P/E_{it} + \varepsilon_{it}$
4. $R_{it} = \alpha_0 + \alpha_1 P_{it} + \varepsilon_{it}$
5. $R_{it} = \alpha_0 + \alpha_1\beta_{it} + \alpha_2 ME_{it} + \varepsilon_{it}$
6. $R_{it} = \alpha_0 + \alpha_1\beta_{it} + \alpha_2 P/E_{it} + \varepsilon_{it}$
7. $R_{it} = \alpha_0 + \alpha_1\beta_{it} + \alpha_2 P_{it} + \varepsilon_{it}$
8. $R_{it} = \alpha_0 + \alpha_1 ME_{it} + \alpha_2 P/E_{it} + \varepsilon_{it}$
9. $R_{it} = \alpha_0 + \alpha_1 ME_{it} + \alpha_2 P_{it} + \varepsilon_{it}$
10. $R_{it} = \alpha_0 + \alpha_1 P/E_{it} + \alpha_2 P_{it} + \varepsilon_{it}$
11. $R_{it} = \alpha_0 + \alpha_1\beta_{it} + \alpha_2 ME_{it} + \alpha_3 P/E_{it} + \varepsilon_{it}$
12. $R_{it} = \alpha_0 + \alpha_1\beta_{it} + \alpha_2 ME_{it} + \alpha_3 P_{it} + \varepsilon_{it}$
13. $R_{it} = \alpha_0 + \alpha_1\beta_{it} + \alpha_2 P/E_{it} + \alpha_3 P_{it} + \varepsilon_{it}$
14. $R_{it} = \alpha_0 + \alpha_1 ME_{it} + \alpha_2 P/E_{it} + \alpha_3 P_{it} + \varepsilon_{it}$
15. $R_{it} = \alpha_0 + \alpha_1\beta_{it} + \alpha_2 ME_{it} + \alpha_3 P/E_{it} + \alpha_4 P_{it} + \varepsilon_{it}$

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

Unlike in other studies where a dummy variable is used for negative P/E ratios, in this study we exclude the negative P/E stocks. According to Fama and French (1992), negative earnings do not proxy the earnings forecasts embedded in the stock price, and the P/E[3] ratio is, therefore, not a proxy for expected returns. However, Fama and French (1992) found confirmation for the hypothesis that firms with negative earnings have higher average returns. Their results also suggest that most of the relation between (positive) P/E and average return is due to the negative correlation between P/E and book-to-market ratios, that is, stocks with low P/E will tend to have high BE/ME[4] ratios. Unfortunately, no data was readily available to enable exploration of this relation for African markets.

The regression results (slope coefficients), however, between P/E and average returns are not significant for four markets, namely, Kenya, Morocco, Tunisia and Zimbabwe. Although not significant, the negative relation between P/E and average returns predicted in the literature is observed only for Kenya and Morocco, when P/E is used alone to explain returns and when used in combination with other explanatory variables. While the P/E slope coefficients are mostly significant for Egypt, they are positive, contrary to the prediction expected. However, the inclusion of both size and beta weakens the explanatory power of P/E ratio (t-statistics is a low 1.6567).

In this study an extra step was taken to investigate the role played by the price level in explaining average stock returns. However, Hawawini and Keim (1995) found the price level to be highly correlated to size (ME) for size-sorted portfolios, that is, a positive correlation coefficient of 0.78 and a t-statistic of 84.94. If this is the case, the stock price will tend to replicate the relation given by size. For Egypt, there is a negative relation between price and average returns. This implies that low-priced stocks tend to give higher returns than high-priced stocks. However, price alone, and when used in conjunction with beta, as an explanatory variable, does not have explanatory power. Other explanatory variables, especially size and the P/E ratio compliment the explanatory power of average price.

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[3] The P/E ratio is used here to maintain consistence, even though Fama & French, 1992 referred to the E/P ratio instead.

[4] Book equity-to-market equity

For Kenya and Tunisia, unlike the Egyptian case, the slope coefficients between price and average returns are positive and significant, whether price is used alone and when used with other explanatory variables. The relation is more significant when beta and the P/E ratio are added into the regression for Kenya, and when price is used alone for Tunisia. However, the positive relationship observed means that high-priced stocks tend to give high returns. For Zimbabwe and Morocco, although positive relations are observed, they are weak. The only significant price slope coefficients are at the 10% level of significance. This is when price is used as the only explanatory variable and when used in combination with size for both markets, and with both size and beta for Morocco.

According to Fama and French (1992), firms with low ME (small-size firms) are more likely to have poor prospects, resulting in low stock prices (and high book-to-market equity). Conversely, large stocks are more likely to be firms with stronger prospects, higher stock prices, lower book-to-market equity, and lower average stock returns. Variables like size, E/P, leverage, and book-to-market equity are all scaled versions of a firm's stock price. From the Fama-MacBeth regressions, Fama and French (1992) found that size, on average, has a negative premium in the cross-section of stock returns and that the average premium for the market beta is essentially zero.

Overall, the results suggest that there is a significant amount of cross-sectional predictability for the three markets: Egypt, Kenya and Tunisia, while for Morocco and Zimbabwe such predictability is relatively absent. This can be observed from the F-statistics in the last columns of Table 9.6.

Evidence in Table 9.7 shows some correlation between some of the explanatory variables used above. For the month-by-month correlations presented in Panel A of the table, the P/E ratio and size are relatively correlated for Egypt (0.38) and for Zimbabwe (0.46). Size is also highly correlated with beta for Morocco (0.51) and for Tunisia (0.40). In Panel B, where overall correlation is considered, significant correlation coefficients, at the 5% level, are observed between size and price for Egypt, Kenya, Morocco and Zimbabwe. For Zimbabwe, all variables are significantly correlated, except between beta and size. The picture given by the correlation matrix can help us understand some of the results discussed in the previous subsections. For example, the size effect for Morocco could be in actual fact a beta effect in disguise.

Table 9.7: Correlation coefficients between variables

Stock market	Panel A – month-by-month correlations				Panel B – correlations based on averages				
		Beta	ln(ME)	P(+)/E		Beta	ln(ME)	P(+)/E	ln(P)
Egypt	Beta	1.00			Beta	1.0000			
	ln(ME)	0.09 [0/64]	1.00		ln(ME)	0.1957	1.0000		
	P(+)/E	0.04 [0/64]	0.38 [41/64]	1.00	P(+)/E	-0.0318	0.5088*	1.0000	
					ln(P)	0.1748	0.4905*	0.2295	1.0000
Kenya	Beta	1.00			Beta	1.0000			
	ln(ME)	0.37 [9/64]	1.00		ln(ME)	0.3680*	1.0000		
	P(+)/E	0.11 [6/64]	0.24 [6/64]	1.00	P(+)/E	-0.1175	0.1032	1.0000	
					ln(P)	0.1450	0.4804*	0.1431	1.0000
Morocco	Beta	1.00			Beta	1.0000			
	ln(ME)	0.51 [64/64]	1.00		ln(ME)	0.4550*	1.0000		
	P(+)/E	-0.20 [0/64]	0.03 [0/64]	1.00	P(+)/E	0.0017	0.1647	1.0000	
					ln(P)	0.5348*	0.6018*	0.0697	1.0000
Tunisia	Beta	1.00			Beta	1.0000			
	ln(ME)	0.40 [33/59]	1.00		ln(ME)	0.4108*	1.0000		
	P(+)/E	-0.01 [2/39]	-0.14 [2/39]	1.00	P(+)/E	0.0495	-0.1836	1.0000	
					ln(P)	0.0781	0.3403	-0.0603	1.0000
Zimbabwe	Beta	1.00			Beta	1.0000			
	ln(ME)	-0.02 [0/64]	1.00		ln(ME)	-0.0005	1.0000		
	P(+)/E	-0.18 [8/64]	0.46 [50/64]	1.00	P(+)/E	-0.4407*	0.5098*	1.0000	
					ln(P)	-0.3303*	0.5734*	0.4327*	1.0000

Marked coefficients (*) are significant at the 5% level
Beta is the trade-to-trade beta, ln(ME) is the natural log of market capitalisation, P(+)/E refers to positive price-earnings ratios, ln(P) is the natural log of the firm's average price for the period under consideration
Fractions in parenthesis in Panel A indicate the number of months with significant correlation coefficients as a proportion of total number of months in the sample.
Source: Chipo Mlambo (2004), University of Stellenbosch Business School

9.6 Conclusion

The chapter investigates the relationship between stock returns and beta, firm size and price-earnings ratios on selected African stock markets for the period 1997 and 2002, all encompassing. Although the period examined is relatively short in comparison to periods investigated in this kind of research for other markets, due to data problems on African stock markets, the results are interesting. The effects observed are mostly in reversed form to those assumed in the literature. A large-firm premium is mostly observed, resulting in a reversed size effect. This is similar to the observation by

Dimson and Marsh (1999) and Horowitz, *et al.* (1999) who concluded that perhaps the size premium may have gone into reverse.

For the P/E effect it is mostly the high P/E portfolios that give the highest returns. These results given by the portfolio analyses are also found using the regression method, where positive slope coefficients are observed for both size and the P/E ratio. While for the month-by-month regressions, none of the average slope coefficients are significant, significance is obtained for the overall regressions using average values of the variables. Ironically, in most cases such significance is contrary to the literature.

There is however, a need for follow-up studies on these two effects for African markets using longer sampling periods and data that does not suffer from survivorship bias. It is also important to investigate the causes of the reversed effects observed in this study. Why is it the case that high risk is associated with low returns on African markets? Why is there a large-firm premium or reversed small-firm effect on African markets? What explains the fact that high P/E stocks give the highest returns? Answers to these and other questions arising from this study need to be unearthed.

10 SEASONAL EFFECTS ON THE FRONTIER AFRICAN STOCK MARKETS

10.1 Introduction

Seasonal anomalies have been the greatest challenge to the Efficient Market Hypothesis (EMH). These are basically irregularities or inconsistencies that conflict with the whole idea that security prices behave in a random manner and that any predictable opportunity for abnormal returns, once publicised, will be arbitraged away into non-existence. Some of the seasonal anomalies have existed for more than a century resulting in doubt on whether stock markets are, in any way, efficient (Cataldo and Savage, 1999). A vast body of literature had investigated the existence and/or persistence of these anomalies and tried to provide explanations thereof. Cataldo and Savage (1999) highlighted some of the key contributors in the anomalies literature. These include Fields (1931, 1934); Gamble (1993); Lakonishok and Smidt (1988); Merrill (1966); Ogden (1990); Schultz (1985) and Wachtel (1942).

Fields (1931, 1934) identified the weekend and holiday effects by finding an opposite pattern to that suggested in popular press reports. These reports suggested that the day preceding a stock exchange holiday or weekend results in speculative readjustment of prices leading to pre-holiday or Friday declines in security prices. Wachtel (1942) identified the turn-of-the-year/January effect and suggested tax-loss selling as one of the possible explanations. This explanation was later empirically confirmed by Schultz (1985). Ogden (1990) developed a liquidity-based hypothesis as a partial explanation for the turn-of-the-month effect. While Merrill (1966) discussed the different seasonal effects, Lakonishok and Smidt (1988) conducted a simultaneous investigation of all seasonal patterns and found persistent evidence for all, but not the month-of-the-year effect using daily Dow Jones Industrial Average (DJIA) data. Gamble (1993) reviewed the literature on seasonal anomalies and suggested that evidence supporting tax-loss selling as an explanation for the January effect is not inconsistent with the intergenerational transfers hypothesis as an explanation.

While seasonal patterns in stock returns have been documented on the US and other markets around the world, on the African markets, according to our knowledge, only the Johannesburg Securities Exchange (JSE) has received relatively considerable attention, compared to the other African markets. Studies on the JSE include Bhana (1985) who found significant negative average returns for Mondays and the highest positive returns on Wednesdays for shares traded on the JSE. Davidson and Meyer (1993) found that the Monday effect was no longer existent on the JSE using the All Share Index for the period 1986 to 1991. Bhana (1994) found mean pre-holiday returns to be much higher than for the other days on the JSE. Bradfield (1990) found significant July and December month-of-the-year effects. Watson and Smit (1994) found at least one significant seasonal effect on each of the South African share market indices they studied.

The latest evidence on the JSE, to our knowledge, is provided by Roux and Smit (2001) who re-examined the different seasonal patterns using the All Share Index, All Gold Index and Financial Index. The purpose was to determine if these anomalies still exist on the JSE. They considered 2 time periods, 1978 to 1989 and 1990 to 1998. The findings suggested that there were significant day-of-the-week (Monday) effects and turn-of-the-year effects in sub-period 1 (in line with earlier research) but these did not persist into sub-period 2. This was taken to suggest that these anomalies are no longer existent on the South African share market. In sub-period 2, there were significant week-of-the-month effects and strong positive turn-of-the-month effects. Further evidence suggested that the Monday effect is caused primarily by Monday returns in the latter part of the month and that the week-of-the-month effect is simply a manifestation of the turn-of-the-month effect.

For the rest of the other African stock markets, only a study by Ayadi, *et al.* (1998) was obtained. The study investigated the January effect on the equity markets of Nigeria, Zimbabwe and Ghana. Using the Kruskal-Wallis and Friedman tests, Ayadi, *et al.* (1998) found no evidence of any seasonal effects on the distribution of stock returns for Nigeria and Zimbabwe. Though the Kruskal-Wallis test suggested an absence of return seasonality on the Ghana Stock Exchange, with the Friedman test, the authors concluded otherwise. To test if average January returns are statistically different from the returns on each of the other eleven months, the Wilcoxon-Mann-Whitney pairwise test was used. The results again showed no January effect in the stock markets of Nigeria and Zimbabwe. For Ghana, the January average return was significantly different from the average returns of February and May (higher) and June, August, October and December (lower). The conclusion that no January effect exist for Nigeria and Zimbabwe, and a January effect exist for Ghana, was reached. Possible explanations suggested for the January effect on the Ghana Stock Exchange include the market's openness to international investors, the dual listing of the Ashanti Goldfields Corporation and the spill over effect from developed markets.

The aim of this chapter is to examine seasonal anomalies on African stock markets. This is particularly important given the little evidence on seasonal anomalies from the frontier African stock markets. The findings can also be used to draw further conclusions on the markets' efficiency.

10.2 The Monday as the Tuesday effect

The most widely examined seasonal effect is the day-of-the-week/weekend effect, which suggests that Mondays provide the lowest negative mean daily returns (Monday effect) and Fridays the highest. On some markets outside the US, Tuesdays were found to provide the lowest mean daily returns. Jaffe and Westerfield (1985) found the lowest mean daily returns for Japan and Australia to occur on Tuesdays. Condoyanni, *et al.* (1987) found that the influence of the US market disguised the indigenous weekend effect in those markets which close before it opens and suggested the existence of negative mean weekend returns in capital markets around the world. Kim (1988) found support for the time zone/lag hypothesis for Korea, Japan and Australia. Aggarwal and Rivoli (1989) found a Tuesday effect on Hong Kong, Singapore, Malaysia and the Philippines over the period September 1976 to June 1988 and explained that this was due to the 13-hour time difference between New York and these Asian markets. The US Monday effect was therefore considered to relate to the Tuesday effect on the Asian markets. Ziemba (1993) identified a Tuesday effect on the Japanese stock market with Tuesday returns negative following a one-day weekend and Monday returns declining after two-day weekends. Dubois and Louvet

(1996) concluded that the negative Monday effect is more likely for the US and UK markets but turns to a Tuesday effect on other markets around the world.

10.3 What explains the existence of seasonal anomalies?

A number of explanations have been suggested as to why seasonal anomalies exist despite the efficiency of the markets.[1] Thaler (1987), for example, proposed factors such as the flow of funds in and out of the market, window dressing by institutional investors, reporting dates and systematic timing of good or bad news as some of the explanations as to why seasonal anomalies exist. French (1980), Rogalski (1984) and Smirlock and Starks (1986) showed that most of the Monday effect occur over the nontrading weekend. They suggested a possible explanation to be that firms tend to release negative information over weekends to avoid panic selling and to allow investors time to assimilate the bad news. The findings by Dyl and Maberly (1988) that unfavourable information is not uniformly distributed over the days of the week supports this hypothesis. This was confirmed by Damodaran (1989) who found that earnings and dividend announcements on Fridays are associated with more reports of declines and negative abnormal returns than announcements made on other days of the week. Fishe, *et al.* (1993) also found the Monday effect to be confined to periods of negative market returns and bad news, and no Monday effect in periods of good news.

Another suggested explanation for the Monday effect is the individual investor hypothesis. Miller (1988), Lakonishok and Maberly (1990) and Abraham and Ikenberry (1994) posited that individual investors who tend to be net sellers of stocks probably make their investment decisions over the weekend resulting in more sell than buy orders on Mondays, especially following bad or negative announcements, and to satisfy liquidity needs. Dyl and Maberly (1992) also found support for the individual investor hypothesis as an explanation for the January effect. Changing investor liquidity positions have been suggested as explanations for some seasonal effects such as the turn-of-the-month effect (Hensel and Ziemba, 1996; Hirsch, 1986; Ogden, 1990). The bulk of monthly cash income in the form of salaries, dividends,

[1] Most of these explanations relate to the weekend effect, which is the most popularly examined seasonal effect

principal payments and debt interest is received at the turn-of-the-month and individuals with surplus cash purchase stocks causing the prices to rise. This liquidity-based hypothesis can also explain the Friday and pre-holiday stock price rises due to the likelihood of salaries/wages being paid before weekends and holidays.

The transactions by individual investors in small firm stocks have been suggested Cataldo and Savage (1999) as explanations why the weekend effect (Abraham and Ikenberry, 1994; Aggarwal and Schatzberg, 1997) and the January effect (Banz, 1981; Basu, 1983; Cook and Rozeff, 1984; Reinganum, 1981) are prevalent for small firm stocks. Eakins and Sewell (1993) and Johnston and Cox (1996) found that small firms with low institutional ownership (or higher proportions of individual ownership) exhibit the highest January returns. Lakonishok and Smidt (1986) found the rates of return for small firms to be eight times those of large firms for the turn-of-the-year. Brauer (1986) suggested that small firms react more severely to information surprises than large firms, probably due to their thin trading nature. Firms neglected by analysts also tend to perform best (Arbel and Strebel, 1982), and though the small firm and neglected firm effects are highly correlated (Arbel and Strebel, 1983), the latter tend to persist over and above the former.

Some findings have also suggested that abnormally low or negative Monday returns seem to follow share market declines over the previous week and that the Monday effect virtually disappears when the market has risen previously (Abraham and Ikenberry, 1994; Agrawal and Tandon, 1994; Cross, 1973; Jaffe, *et al.*, 1989b; Liano, *et al.*, 1993). Others have suggested that the weekend effect is related to patterns in the distribution of dividends with most firms having a tendency to go ex-dividend on Mondays resulting in a more pronounced weekend effect (Choy and O'Hanlon, 1989; Phillips-Patrick and Schneeweis, 1988; Theobold and Price, 1984).

The most popular explanation for the January effect, particularly on the US markets, is tax-loss selling whereby an investor (taxpayer) may sell a stock that has declined in value to below cost to realise a tax loss, while remaining invested in a stock that has risen in value to defer taxable gains realisation (Cataldo and Savage, 1999). This proposition was supported in studies by Jones, *et al.* (1987); Jones, *et al.* (1991);

Schultz (1985) and Brailsford and Easton (1993) while Givoly and Ovadia (1983); Slemrod (1982) and Brauer and Chang (1990) suggested tax loss-selling to be one possible explanation for their results of a December decline followed by a January rise.

Other explanations for the January effect include the ITH (Dyl and Maberly, 1992; Wachtel, 1942), particularly in countries that do not have capital gains tax differentials but that do celebrate the Christmas gift-giving season (Gamble, 1993). The ITH is defined as a liquidity preference-based demand for cash to buy gifts during the Christmas gift-giving season (Wachtel, 1942) and/or the transfer of wealth from older, risk-averse investors, to younger, less risk-averse investors. This is hypothesised to occur around the Christmas gift-giving season. Older investors might liquidate their large value-weighted firm stocks and give the cash to younger investors or alternatively young investors might liquidate large-firm stocks received as gifts and re-invest the proceeds in riskier, small firm stocks. The older investor would sell the losers for loss recognition and would retain the winners to lock in gains, and for a tax-free transfer of wealth at death.

The literature explaining the existence of seasonal effects is so abundant such that the review above is far from being exhaustive. Making an exhaustive review of literature is beyond the scope of this chapter, the aim of which is to contribute to the body of knowledge by extending the investigations of seasonal anomalies[2] to African stock markets. This is particularly important given the little evidence on seasonal anomalies from the African markets. The findings can also be used to reflect further on the efficiency of these markets.

[2] Cataldo and Savage (1999) suggest that, though initially perceived as anomalous, these predictable seasonal patterns cease to be so with their monograph, which provides a common theoretical framework. This paradigm shift is based on Keynes' theory of investor liquidity preferences in his work entitled "The General Theory of Employment Interest and Money". The explanations given to the seasonal effects can now be related to any of the three motivating factors for investor liquidity, that is, transaction, precautionary and speculative motives.

10.4 Data and methodology

Continuously compounded returns computed from daily closing price indices from 9 African stock markets are used. These returns are computed as follows:

$$R_t = \ln(I_t) - \ln(I_{t-1}) \qquad (10.1)$$

where R_t = is the return on the index for day t

I_t = value of the index at the close of day t

I_{t-1} = value of the index on the previous day, t-1

The data for these indices was obtained from the respective stock exchanges. The periods of analysis range from 4 years 3 months (September 1998 to December 2002) for the BRVM in Cote d'Ivoire to 6 years (January 1997 to December 2002) for Egypt, Morocco and Zimbabwe. All the markets covered were trading daily at the end of the period except Ghana, which traded (and still trades)[3] only three times a week. For the BRVM, though the period covered begins at inception, the market only turned to daily trading beginning November 2001. The same applies for Mauritius, which shifted to daily trading beginning November 1997. However, unlike for the BRVM, most of the data for Mauritius came from the period of daily trading. While Ghana is excluded from the day-of-the-week/weekend analysis, the BRVM and Mauritius are only analysed for the respective periods of daily trading.

Table 10.1 reports the descriptive statistics for the calculated daily returns. The number of data points (returns) ranges from 753 for Ghana to 1499 for Zimbabwe. The mean returns are positive for all the Indices except Namibia's Local Index and the BRVM and Egyptian Indices.

Table 10.1 show that the returns for all the indices are heavily skewed and have excess kurtosis. The Kolmogorov-Smirnov test statistics suggest a rejection of the normality assumption (at the 1% level) for all the indices in the 9 countries. The use

[3] As at 31 December 2003

of parametric tests such as OLS regression in the presence of violations of the OLS assumptions is discouraged. However, much of the earlier research on anomalies has used this methodology, which is acceptable in mild form violations and especially in large data samples. According to Kunkel, *et al.* (2003, p212), a study by Ittenbach, *et al.* (1993) found the patterns of significance and statistical power of parametric and nonparametric analysis of variance (ANOVA) procedures to be almost identical in three of the four approaches they studied, with the nonparametric multivariate ANOVA procedure showing a slight advantage over the other techniques.

Table 10.1: General and descriptive statistics for stock index returns

		(a) Descriptive Statistics						(b) Period Investigated
Stock market	Stock Index	# Obs.	Mean (%)	SD (%)	Skewness	Kurtosis	K-S*	
Botswana	Domestic	1177	0.098	0.622	2.270	16.569	6.940**	23-Mar-98 to 31-Dec-02
	Foreign	1177	0.044	2.547	-1.447	25.919	11.053**	
	All	1177	0.049	2.403	-1.421	25.979	10.978**	
BRVM	BRVM-10	752	-0.027	0.970	-0.750	6.122	4.139**	16-Sep-98 to 31-Dec-02
	BRVM-C	752	-0.040	0.692	-0.158	5.225	3.292**	
Egypt	HFI	1489	-0.047	1.317	0.160	1.158	2.806**	02-Jan-97 to 31-Dec-02
	EFGI	1489	-0.047	1.398	0.106	1.085	2.616**	
Ghana	GSE	753	0.133	1.251	2.506	39.098	6.733**	02-Jan-98 to 30-Dec-02
Mauritius	SEMDEX	1401	0.009	0.441	0.703	8.692	3.396**	06-Jan-97 to 31-Dec-02
	SEMTRI	1401	0.037	0.441	0.756	8.815	3.563**	
Morocco**	CFG25	1493	0.002	0.634	0.821	8.327	3.892**	02-Jan-97 to 31-Dec-02
Namibia	Overall	1459	0.022	2.219	-1.542	111.866	7.019**	06-Jan-97 to 31-Dec-02
	Local	1459	-0.081	2.130	-0.820	145.739	10.988**	
Tunisia	BVMT	1249	0.043	0.858	0.154	1.541	3.226**	02-Jan-98 to 31-Dec-02
	TUNINDEX	1249	0.009	0.535	1.017	12.617	3.231**	
Zimbabwe	Industrial	1499	0.164	1.741	-0.581	12.973	4.575**	02-Jan-97 to 31-Dec-02
	Mining	1499	0.118	3.165	-0.335	11.627	6.716**	

* All Kolmogorov-Smirnov Z-statistics are significant at less than the 1% level suggesting a strong rejection of the normality assumption
**For Morocco only one index was used in the analysis, the CFG25. This is because the MASI and MADEX are fairly new and data for the no-longer-existent IGB could not be obtained.
The mean and standard deviation statistics were multiplied by 100 to give a percentage return since in their numerical values, the mean figures were almost identically zero when rounded to decimal 3.
Source: Chipo Mlambo (2004), University of Stellenbosch Business School

The violation of the normality assumption would suggest use of nonparametric tests more appropriate. However, with regression on 'dummy' variables, a manipulation of the coefficients will give the mean daily returns, and thus enable a descriptive interpretation of the results. With the deviations from normality, however, the statistical significance of the t-statistics will be unreliable.

10.5 Regression results

10.5.1 Day-of-the-week/Monday effect

The day-of-the-week (DOW) effect suggests that Mondays provide the lowest mean daily returns and Fridays the highest. The weekend effect, therefore, implies a tendency for higher Friday and lower Monday mean daily returns. To examine the DOW effect using regression analysis, the following model is estimated:

$$R_t = \beta_1 + \beta_2 Tue_t + \beta_3 Wed_t + \beta_4 Thu_t + \beta_5 Fri_t + \varepsilon_t \qquad (10.2)$$

Where R_t is the return on day t, the constant, β_1, represent the Monday mean daily return[4], β_2 is the response coefficient for the dummy variable Tue_t, β_3 is the response coefficient for the dummy variable Wed_t, β_4 is the response coefficient for the dummy variable Thu_t, β_5 is the response coefficient for the dummy variable Fri_t. The null hypothesis is that there are no differences between mean returns for each day of the week. The results of regression model 10.2 are presented in Panel (a) of Table 10.2.

To further examine the Monday effect, which suggests that Monday mean daily returns are lowest and/or more negative than returns for all the other days of the week, equation (10.2) is simplified by using only one dummy variable, taking the value of 1 on Mondays and 0 otherwise. The following regression model is estimated:

$$R_t = \alpha_0 + \alpha_1 Mon_t + e_t \qquad (10.3)$$

where the constant α_0 represent returns for all the other days of the week, except Monday, and α_1 is a coefficient for the dummy variable taking the value of 1 on

[4] The mean daily returns for Tuesday, Wednesday, Thursday and Friday will be equal to the values of the coefficients for the respective days plus the Monday mean daily return. Alternatively we could have used a regression equation without an intercept but which includes a Monday dummy as an additional explanatory variable. In the alternative each coefficient would then have been equal to the mean daily return for the respective day.

Mondays and 0 otherwise. The null hypothesis is that there are no differences in mean returns between Monday and all the other days of the week. The results for this regression equation are presented in Panel (b) of Table 10.2.

Table 10.2: Regression results for day-of-the-week/Monday effect

Stock Exchange	Index		(a)						(b)		
			(C=MON)	TUE	WED	THU	FRI	F-stat	(C=ROW)	MON	F-stat
Botswana	Domestic	coef. (%)	0.045	0.097	**0.106**	***-0.018***	0.079	2.033	0.110**	***-0.066***	2.060
		t-stat	1.090	1.687	1.839	-0.315	1.369		5.468	-1.435	
	Foreign	coef. (%)	***-0.330****	0.358	0.556*	0.278	**0.673****	2.440*	0.135	***-0.465****	6.171*
		t-stat	-1.966	1.522	2.368	1.183	2.844		1.632	-2.484	
	All Companies	coef. (%)	***-0.307***	0.340	0.530*	0.258	**0.648****	2.542*	0.135	***-0.443****	6.284*
		t-stat	-1.941	1.529	2.393	1.167	2.902		1.736	-2.507	
BRVM	BRVM-10	coef. (%)	0.069	**0.063**	0.019	***-0.189***	0.014	0.656	0.045	***0.024***	0.030
		t-stat	0.569	0.370	0.111	-1.102	0.082		0.742	0.174	
	BRVM-Comp	coef. (%)	**0.069**	-0.029	-0.001	***-0.125***	-0.016	0.404	***0.026***	0.043	0.225
		t-stat	0.842	-0.248	-0.008	-1.080	-0.138		0.620	0.474	
Egypt[#]	HFI	coef. (%)	-0.087	0.052	***-0.059***	0.068	**0.137**	0.934	-0.037	***-0.049***	0.333
		t-stat	-1.133	0.479	-0.544	0.630	1.267		-0.981	-0.577	
	EFGI	coef. (%)	-0.111	0.130	***-0.071***	0.104	**0.158**	1.415	-0.032	***-0.079***	0.767
		t-stat	-1.369	1.124	-0.620	0.909	1.376		-0.782	-0.876	
Mauritius	SEMDEX	coef. (%)	-0.004	-0.010	0.008	***-0.012***	**0.039**	0.588	0.003	***-0.006***	0.042
		t-stat	-0.135	-0.256	0.217	-0.329	1.018		0.186	-0.205	
	SEMTRI	coef. (%)	0.029	***-0.019***	0.000	-0.011	**0.035**	0.587	0.030*	***-0.002***	0.003
		t-stat	1.071	-0.492	0.012	-0.279	0.925		2.263	-0.052	
Morocco	CFG25	coef. (%)	-0.067	***-0.018***	0.103*	**0.158****	0.103*	4.214**	0.020	***-0.087****	4.546*
		t-stat	-1.836	-0.345	1.996	3.063	1.999		1.089	-2.132	
Namibia	Overall	coef. (%)	-0.015	0.013	**0.277**	***-0.193***	0.083	1.710	0.027	***-0.025***	0.029
		t-stat	-0.116	0.073	1.511	-1.051	0.449		0.410	-0.171	
	Local	coef. (%)	-0.057	***-0.096***	**0.056**	0.014	-0.095	0.302	***-0.088***	0.035	0.060
		t-stat	-0.457	-0.546	0.319	0.081	-0.535		-1.413	0.246	
Tunisia	BVMT	coef. (%)	0.030	***-0.043***	**0.070**	0.045	-0.007	0.678	0.047	***-0.016***	0.072
		t-stat	0.561	-0.566	0.913	0.581	-0.091		1.717	-0.268	
	TUNINDEX	coef. (%)	0.032	***-0.067***	-0.033	**0.016**	-0.032	0.909	***0.004***	0.029	0.584
		t-stat	0.959	-1.397	-0.687	0.340	-0.672		0.207	0.765	
Zimbabwe	Industrial	coef. (%)	***0.031***	0.136	**0.182**	0.165	0.177	0.558	0.196**	***-0.165***	2.110
		t-stat	0.308	0.951	1.277	1.154	1.229		3.918	-1.452	
	Mining	coef. (%)	***-0.072***	0.144	0.289	0.039	**0.478**	1.140	0.164	***-0.236***	1.305
		t-stat	-0.388	0.553	1.116	0.149	1.830		1.800	-1.142	

Panel (a) and panel (b) present the regression results, that is, the regression coefficients, t and F statistics for the following equations, respectively:

$$R_t = \beta_1 + \beta_2 Tue_t + \beta_3 Wed_t + \beta_4 Thu_t + \beta_5 Fri_t + \varepsilon_t$$

$$R_t = \alpha_0 + \alpha_1 Mon_t + e_t$$

All coefficients have been presented as percentages (multiplied by 100) since most of them became almost zero after rounding to decimal 3. This could have been avoided from the outset by calculating rates of return as percentages rather than as fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold and "Bold Italic" denote the regression coefficients for the days of the week that give the highest and lowest mean daily returns, respectively. Note that in Panel (b) only the coefficients that give the lowest mean daily returns have been marked in bold italic.

[#] The trading week for Egypt funs from Sunday to Thursday such that Monday in the table refers to Sunday, Tuesday to Monday, Wednesday to Tuesday, etc. on the Egyptian Stock Exchange

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

The results indicate that Mondays give the lowest mean daily returns for Botswana's Foreign Companies Index (FCI) and the All Companies Index (ACI), and for Zimbabwe's Industrial and Mining indices, consistent with literature. However, only the Monday returns for the FCI are significant at the 5% level. The lowest mean daily returns are observed on a Tuesday for Mauritius' SEMTRI, Morocco's CFG25, Namibia's Local Index, and Tunisia's BVMT and TUNINDEX, consistent with evidence from the Australian and Asian markets (e.g. Aggarwal and Rivoli, 1989; Dubois and Louvet, 1996; Jaffe, *et al.*, 1989b; Kim, 1988; Ziemba, 1993). For the

Egyptian Financial Group Index (EFGI) and the Hermes Financial Index (HFI), the lowest mean daily returns are observed on a Wednesday[5]. For the remaining indices, that is, the BRVM-Composite and BRVM-10 indices, Botswana's Domestic Companies Index (DCI), Mauritius' SEMDEX, and Namibia's Overall Index, the lowest mean daily returns fall on a Thursday. However, none of the lowest mean daily returns are observed on a Friday for all the indices.

The largest mean daily returns are observed on a Friday for the FCI and ACI (significant at the 1% level), Zimbabwe's Mining Index, Egypt's HFI and EFGI[6], and Mauritius' SEMTRI and SEMDEX. Although not all of them are significant, the evidence support the literature that Fridays give the highest mean daily returns as compared to the other days of the week. For the other indices, the highest mean daily returns are observed on Monday for the BRVM-Composite, Tuesday for the BRVM-10, Wednesday for Botswana's DCI, Namibia's Overall and Local indices, the BVMT and Zimbabwe's Industrial Index, and on a Thursday for the TUNINDEX and Morocco's CFG25 (significant at the 1% level). For the CFG25, Wednesday and Friday also provide significantly positive mean daily returns. The mean daily returns for the FCI and ACI are also positive and significant on a Wednesday.

In Panel (b) of Table 10.2, a significant Monday effect is observed for the ACI, FCI and CFG25 indices. A Monday effect (but not significant at the 5% level) is also observed for all the other indices, except, the BRVM-Composite, Namibia's Local Index and the TUNINDEX. The rest-of-the-week (ROW) mean daily returns are significantly positive for the DCI, the SEMTRI, and Zimbabwe's Industrial Index.

10.5.2 End/turn-of-the-month effect

The end-of-the-month (EOM) refers to the last trading day of the month while the turn-of-the-month (TOM) refers to the last trading day of the previous month plus the first four trading days of the current month. These five consecutive trading days are

[5] Literally, on a Tuesday according to the trading week for the Egyptian Stock Exchange which runs from Sunday to Thursday.

[6] Literally, on a Thursday according to the trading week for the Egyptian Stock Exchange which runs from Sunday to Thursday.

hypothesised to distinctly outperform the rest of the month (Merrill, 1966) due to investors' tendency to operate on a monthly fiscal basis (Hirsch, 1986). Merrill (1966) suggested that buying for profit before the last 3 days of the month and selling after the first 3 days of the month could be profitable. The turn-of-the-month effect is examined using the following regression analysis:

$$R_t = \beta_0 + \beta_1 EOMN1_t + \sum_{i=1}^{4} \beta_{i+1} EOMPi_t + \varepsilon_t \qquad (10.4)$$

where the constant β_0 represent the mean daily return for all the other days of the month, β_1 is the coefficient of the dummy variable taking the value of 1 on the last day of the previous month and 0 otherwise, β_{i+1} is a coefficient for the dummy variable, taking the value of 1 on the i^{th} day of the current month and 0 otherwise. The null hypothesis is to test that there is no difference between mean returns for each of the turn-of-the-month days and for all the other days of the month. The results of this regression model are presented in Panel (a) of Table 10.3.

The TOM effect is further investigated using a regression equation with one dummy explanatory variable taking the value of 1 on each of the TOM days and 0 otherwise. This regression equation is specified as follows:

$$R_t = \alpha_0 + \alpha_1 TOM_t + e_t \qquad (10.5)$$

where the constant α_0 represent the mean daily returns for all the other days of the month that are not TOM and α_1 is the coefficient for the dummy variable taking the value of 1 on a TOM day and 0 otherwise. The estimated coefficients for this equation are presented in Panel (b) and (c) of Table 10.3. The results in Panel (c) are the TOM effects after extracting the January TOM/turn-of-the-year effect.

Table 10.3: Regression results for end/turn-of-the-month effect

Stock Exchange	Index		(a)							(b)			(c)		
			(C=ODM)	EOMN1	EOMP1	EOMP2	EOMP3	EOMP4	F-stat	(C=ROM)	TOM	F-stat	(C=ROM2)	TOM2	**F-stat**
Botswana	Domestic	coef. (%)	0.096**	-0.029	**0.071**	***-0.046***	0.002	0.036	0.271	0.096**	**0.007**	0.024	0.096**	**0.008**	0.035
		t-stat	4.602	-0.343	0.831	-0.544	0.025	0.419		4.607	0.155		4.650	0.186	
	Foreign	coef. (%)	***-0.064***	0.193	0.486	**0.731***	0.401	0.424	1.597	-0.064	**0.446****	6.673**	-0.059	**0.457****	6.647**
		t-stat	-0.752	0.559	1.398	2.104	1.155	1.219		-0.753	2.583		-0.697	2.578	
	All Companies	coef. (%)	***-0.055***	0.179	0.470	**0.689***	0.417	0.400	1.656	-0.055	**0.430****	6.974**	-0.050	**0.442****	6.983**
		t-stat	-0.690	0.551	1.433	2.102	1.271	1.221		-0.691	2.641		-0.636	2.643	
BRVM	BRVM-10	coef. (%)	-0.016	**0.173**	-0.070	-0.098	-0.033	***-0.135***	0.677	**-0.016**	-0.032	0.180	**-0.013**	-0.044	0.336
		t-stat	-0.376	1.223	-0.488	-0.688	-0.228	-0.945		-0.376	-0.424		-0.313	-0.580	
	BRVM-Comp	coef. (%)	-0.024	**0.084**	-0.072	***-0.139***	-0.013	-0.103	0.816	**-0.024**	-0.048	0.810	**-0.020**	-0.064	1.373
		t-stat	-0.767	0.833	-0.704	-1.361	-0.130	-1.009		-0.768	-0.900		-0.665	-1.172	
Egypt	HFI	coef. (%)	***-0.090****	0.189	0.194	0.072	0.190	**0.230**	1.084	-0.090*	**0.175***	4.835*	-0.066	**0.086**	1.095
		t-stat	-2.285	1.180	1.214	0.451	1.187	1.435		-2.288	2.199		-1.713	1.046	
	EFGI	coef. (%)	***-0.096****	0.222	0.224	0.106	0.152	**0.302**	1.299	-0.096*	**0.201***	5.678*	-0.077	**0.133**	2.324
		t-stat	-2.312	1.305	1.321	0.626	0.896	1.778		-2.314	2.383		-1.874	1.524	
Ghana	GSE Index	coef. (%)	0.155**	**0.140**	-0.009	-0.140	***-0.294***	0.030	0.925	**0.155****	-0.055	0.347	**0.158****	-0.067	0.498
		t-stat	2.639	0.813	-0.051	-0.817	-1.711	0.175		2.638	-0.589		2.753	-0.705	
Mauritius	SEMDEX	coef. (%)	***-0.007***	0.072	0.086	0.001	0.034	**0.103**	1.464	-0.007	**0.059***	4.789*	-0.003	**0.051**	3.322
		t-stat	-0.478	1.342	1.589	0.014	0.627	1.916		-0.478	2.188		-0.247	1.823	
	SEMTRI	coef. (%)	0.021	0.070	0.103	***-0.005***	0.031	**0.107***	1.717	0.021	**0.061***	5.138*	0.025	**0.050**	3.271
		t-stat	1.541	1.311	1.906	-0.098	0.569	2.001		1.542	2.267		1.847	1.809	
Morocco	CFG25	coef. (%)	0.013	0.051	***-0.226****	-0.084	**0.070**	-0.037	2.307*	**0.013**	-0.045	1.363	**0.007**	-0.022	0.318
		t-stat	0.706	0.668	-2.926	-1.094	0.907	-0.484		0.705	-1.167		0.399	-0.564	
Namibia	Overall	coef. (%)	0.016	0.044	0.130	***-0.168***	-0.016	**0.134**	0.188	0.016	**0.024**	0.033	0.015	**0.031**	0.051
		t-stat	0.234	0.163	0.477	-0.622	-0.060	0.496		0.234	0.181		0.221	0.227	
	Local	coef. (%)	-0.086	-0.056	0.078	***-0.457***	**0.323**	0.215	1.171	-0.086	**0.020**	0.025	-0.087	**0.025**	0.034
		t-stat	-1.341	-0.216	0.298	-1.766	1.249	0.831		-1.341	0.158		-1.367	0.185	
Tunisia	BVMT	coef. (%)	0.047	***-0.144***	**0.111**	0.012	0.063	-0.108	0.789	**0.047**	-0.014	0.056	**0.046**	-0.014	0.055
		t-stat	1.674	-1.261	0.968	0.107	0.548	-0.944		1.674	-0.237		1.688	-0.235	
	TUNINDEX	coef. (%)	0.009	0.024	**0.064**	***-0.034***	-0.026	-0.016	0.281	0.009	**0.002**	0.004	**0.010**	-0.003	0.006
		t-stat	0.504	0.342	0.894	-0.471	-0.366	-0.226		0.504	0.066		0.579	-0.075	
Zimbabwe	Industrial	coef. (%)	0.163**	0.021	-0.141	**0.257**	0.121	***-0.227***	0.721	0.163**	**0.007**	0.004	**0.180****	-0.073	0.455
		t-stat	3.151	0.100	-0.662	1.214	0.570	-1.071		3.152	0.063		3.540	-0.675	
	Mining	coef. (%)	0.115	0.149	***-0.278***	-0.005	**0.428**	-0.238	0.486	0.115	**0.012**	0.004	**0.138**	-0.091	0.214
		t-stat	1.227	0.388	-0.718	-0.012	1.112	-0.618		1.227	0.063		1.492	-0.463	

Panel (a) and panels (b) and (c) present the regression results, that is, the regression coefficients, t and F statistics for the following equations, respectively:

$$R_t = \beta_0 + \beta_1 EOMN1_t + \sum_{i=1}^{4} \beta_{i+1} EOMPi_t + \varepsilon_t$$

$$R_t = \alpha_0 + \alpha_1 TOM_t + e_t$$

All coefficients have been presented as percentages (multiplied by 100) since most of them became almost zero after rounding to decimal 3. This could have been avoided from the outset by calculating rates of return as percentages rather than as fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold and "Bold Italic" denote the regression coefficients for the days of the month that give the highest and lowest mean daily returns, respectively. Note that in Panel (b) only the coefficients that give the highest mean daily returns have been marked in bold.

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

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Panel (a) of Table 10.3 shows that none of the markets has a significant EOM effect. However, most of the indices exhibit positive mean daily returns for the EOM, except for Botswana's DCI, Namibia's Local Index and Tunisia's BVMT. The EOM mean daily returns are highest only for the BRVM-10, BRVM-Composite and the GSE Index and lowest for the BVMT. The EOM effect is, therefore, very weak on the African markets. Of the TOM days, significantly positive mean daily returns (at the 5% level) are observed only on Botswana's FCI and ACI on the second trading day of the month and on Mauritius's SEMTRI on the fourth trading day of the month. For Morocco's CFG25, the first day of the month provides significantly negative (at the 1% level) mean daily returns. The other days of the month seem to significantly explain the mean daily returns for Botswana's DCI, the Ghana Index and Zimbabwe's Industrial Index (positive at the 1% level), and for Egypt's HFI and EFGI (negative at the 5% level).

The TOM analysis in Panel (b) of Table 10.3, suggest a significant TOM effect for Botswana's FCI and ACI (at the 1% level), Egypt's HFI and EFGI, and Mauritius's SEMDEX and SEMTRI (at the 5% level). No significant TOM effect is observed for the BRVM, Ghana, Morocco and Tunisia's BVMT. For Namibia's Local Index, the TOM seems to give the highest, but not significant, mean daily return. After extracting the TOY effect from the series, the TOM effect remains significant for Botswana's FCI and ACI, but becomes insignificant for all the other markets (see Table 10.2 Panel (c)). The results therefore, suggest that apart from Botswana, the TOM effect observed on the other markets is driven by the TOY effect.

10.5.3 End/turn-of-the-year effect

The pattern suggested by the January effect is that stock returns are, on average higher in the first few trading days of the year ranging from four to about ten trading days in January. While the end-of-the-year (EOY) and turn-of-the-year (TOY) effects follow similarly, the former refers to the last trading day of the year and the latter refers to the last trading day of the year plus the first four trading days in January. The EOY/TOY effects are examined using regression equations similar to those used for the EOM/TOM effects, with the only difference being the definitions of the dummy variables. Each TOY mean-daily return is examined using the following regression equation:

$$R_t = \beta_0 + \beta_1 JANN1_t + \sum_{i=1}^{4} \beta_{i+1} JANPi_t + \varepsilon_t \qquad (10.6)$$

where the constant β_0 represent the average return for all the other days of the year, β_1 is the coefficient of the dummy variable that takes the value of 1 on the last day of the previous year and 0 otherwise, β_{i+1} is a coefficient for the dummy variable, taking the value of 1 on the i^{th} day in January and 0 otherwise.

Table 10.4: Regression results for end/turn-of-the-year effect

Stock Exchange	Index		(a)							(b)		
			(Ct=ODY2)	JANN1	JANP1	JANP2	JANP3	JANP4	F-stat	(C=ROY)	TOY	F-stat
Botswana	Domestic	coef. (%)	0.098**	**0.264**	-0.015	-0.039	***-0.241***	-0.097	0.322	0.098**	-0.012	0.007
		t-stat	5.340	0.945	-0.047	-0.125	-0.772	-0.311		5.346	-0.086	
	Foreign	coef. (%)	0.042	***-1.063***	-0.042	1.128	-0.628	**1.560**	0.679	0.042	**0.131**	0.055
		t-stat	0.560	-0.931	-0.033	0.884	-0.492	1.222		0.560	0.234	
	All Companies	coef. (%)	0.047	***-1.001***	-0.043	1.071	-0.613	**1.441**	0.671	0.047	**0.115**	0.047
		t-stat	0.664	-0.929	-0.036	0.889	-0.509	1.196		0.665	0.217	
BRVM	BRVM-10	coef. (%)	-0.030	1.192**	0.121	-0.143	***-0.550***	-0.454	1.983	-0.030	**0.088**	0.169
		t-stat	-0.829	2.746	0.250	-0.294	-1.135	-0.936		-0.826	0.411	
	BRVM-Comp	coef. (%)	-0.043	1.099**	0.042	-0.125	***-0.369***	-0.353	3.026**	-0.043	**0.108**	0.499
		t-stat	-1.699	3.564	0.121	-0.363	-1.070	-1.026		-1.687	0.706	
Egypt	HFI	coef. (%)	*-0.065*	0.795	1.552**	0.780	1.153*	0.093	3.423**	-0.065	0.875**	13.060**
		t-stat	-1.888	1.482	2.891	1.452	2.149	0.173		-1.888	3.614	
	EFGI	coef. (%)	-0.062	0.926	1.470**	0.641	0.822	***-0.320***	2.566*	-0.062	0.708**	7.570**
		t-stat	-1.691	1.623	2.577	1.124	1.441	-0.561		-1.690	2.751	
Ghana	GSE Index	coef. (%)	0.131**	**0.747**	-0.009	-0.085	-0.123	***-0.167***	0.387	0.131**	**0.076**	0.086
		t-stat	2.816	1.328	-0.014	-0.150	-0.218	-0.297		2.820	0.294	
Mauritius	SEMDEX	coef. (%)	0.006	***-0.033***	-0.012	0.124	0.182	**0.247**	0.674	0.006	**0.105**	1.622
		t-stat	0.538	-0.184	-0.060	0.686	1.008	1.365		0.538	1.273	
	SEMTRI	coef. (%)	0.034**	0.131	***-0.021***	0.123	0.155	**0.230**	0.667	0.034**	**0.129**	2.419
		t-stat	2.856	0.726	-0.108	0.680	0.861	1.275		2.859	1.555	
Morocco	CFG25	coef. (%)	0.007	-0.359	-0.624*	-0.223	**0.121**	-0.121	1.578	**0.007**	-0.228	3.685
		t-stat	0.418	-1.384	-2.200	-0.860	0.468	-0.469		0.418	-1.920	
Namibia	Overall	coef. (%)	0.023	**0.931**	-0.096	***-0.836***	-0.394	0.135	0.425	**0.023**	-0.051	0.015
		t-stat	0.386	1.024	-0.096	-0.921	-0.433	0.148		0.387	-0.122	
	Local	coef. (%)	-0.081	1.001	-0.461	-5.054**	4.327**	-0.017	12.500**	-0.081	**-0.026**	0.004
		t-stat	-1.458	1.171	-0.493	-5.914	5.064	-0.019		-1.430	-0.065	
Tunisia	BVMT	coef. (%)	0.043	-0.141	***-0.181***	-0.050	0.011	**0.301**	0.189	**0.043**	-0.005	0.001
		t-stat	1.771	-0.366	-0.422	-0.129	0.028	0.783		1.773	-0.028	
	TUNINDEX	coef. (%)	0.008	0.145	-0.090	***-0.108***	-0.086	**0.350**	0.588	0.008	**0.048**	0.188
		t-stat	0.549	0.605	-0.334	-0.451	-0.356	1.457		0.549	0.433	
Zimbabwe	Industrial	coef. (%)	0.150**	1.219	1.057	**1.356**	0.138	***-0.085***	1.680	0.150**	0.726*	4.960*
		t-stat	3.309	1.713	1.357	1.907	0.194	-0.119		3.310	2.227	
	Mining	coef. (%)	0.100	4.044**	1.580	-0.223	***-0.305***	-0.274	2.233*	0.100	**0.943**	2.528
		t-stat	1.211	3.130	1.116	-0.173	-0.236	-0.212		1.209	1.590	

Panel (a) and panel (b) present the regression results, that is, the regression coefficients, t and F statistics for the following equations, respectively:

$$R_t = \beta_0 + \beta_1 JANN1_t + \sum_{i=1}^{4} \beta_{i+1} JANPi_t + \varepsilon_t$$

$$R_t = \alpha_0 + \alpha_1 TOY_t + e_t$$

All coefficients have been presented as percentages (multiplied by 100) since most of them became almost zero after rounding to decimal 3. This could have been avoided from the outset by calculating rates of return as percentages rather than as fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold and "Bold Italic" denote the regression coefficients for the days of the year that give the highest and lowest mean daily returns, respectively. Note that in Panel (b) only the coefficients that give the highest mean daily returns have been marked in bold.

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

The null hypothesis is to test that there is no difference between the mean daily returns for each of the turn-of-the-year days and all the other days of the year. The results of this regression model are presented in Panel (a) of Table 10.4.

The TOY effect is further investigated using a regression equation with one dummy explanatory variable taking the value of 1 on each of the TOY days and 0 otherwise, specified as follows:

$$R_t = \alpha_0 + \alpha_1 TOY_t + e_t \qquad (10.7)$$

where the constant α_0 represent returns for all the non-TOY days and α_1 is the coefficient for the dummy variable taking the value of 1 on a TOY day and 0 otherwise. The results for this equation are presented in Panel (b) of Table 10.4.

A significant EOY effect is observed on the BRVM's two indices, the BRVM-10 and the BRVM-Composite, and on Zimbabwe's Mining Index. In both cases the coefficients are significant at the 1% level suggesting a strong EOY effect for these indices on the two markets. For the other TOY days, the highest and significantly positive (at the 1% level) mean daily returns are observed on the first trading day in January for Egypt's HFI and EFGI Indices, and on the third trading day in January for Namibia's Local Index. Namibia's Local Index, however, exhibits the lowest and significantly negative mean daily return on the second trading day in January. Morocco's CFG25 also has the lowest and significantly negative mean daily return on the first trading day in January.

Panel (b) of Table 10.4 confirms the TOY effect for Egypt's two indices at the 1% level. Zimbabwe's Industrial Index also exhibits the TOY effect at the 5% level, using regression equation (10.7) but the Mining Index ceases to be significant. Weak TOY effects are also observed on other indices but they are not significant. Therefore, of all the indices in this analysis, only the Egyptian indices and Zimbabwe's Industrial Index seem to have strong TOY effects.

10.5.4 Month-of-the-year effect

With the month-of-the-year (MOY) effect, evidence from the US markets (see Cataldo and Savage, 1999) suggests that the three-month sequence, November, December and January provide the most favourable mean daily returns. Another MOY related hypothesis is the 'December decline followed by January rise' sequence observed on some markets[1]. To examine the MOY effect using regression analysis, the following model is estimated:

$$R_t = \beta_1 + \beta_2 Feb_t + \beta_3 Mar_t + \beta_4 Apr_t + \beta_5 May_t + ... + \beta_{12} Dec_t + \varepsilon_t \qquad (10.8)$$

where the constant β_1 represent the January mean daily return, β_2 is the coefficient of the dummy variable that takes the value of 1 in February and 0 otherwise, β_3 is a coefficient for the dummy variable, taking the value of 1 in March and 0 otherwise, and so forth. The null hypothesis is that all the regression coefficients are zero. The results are presented in Panel (a) of Table 10.5.

The literature suggests that January provides the highest and significantly positive mean daily returns compared to the other months of the year. These positive mean daily returns are hypothesised to occur in the first few days in January. To further examine if January provides significantly positive returns in comparison to all the other months of the year, a simplified, one dummy variable regression model is used. This is formulated as follows:

$$R_t = \alpha_0 + \alpha_1 Jan_t + e_t \qquad (10.9)$$

where the constant α_0 represent returns for all the other months of the year and α_1 is the coefficient for the dummy variable taking the value of 1 in January and 0 otherwise. The estimated coefficients for this equation are presented in Panel (b) of Table 10.5.

[1] The hypothesis also suggests that the decline in December takes place in the last few days of the month, and the rise in January takes place in the first few days in January.

Table 10.5: Regression results for month-of-the-year/January effect

Stock Exchange	Index		(a)													(b)		
			(C=JAN)	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	F-stat	(C=OMY)	JAN	F-stat
Botswana	Domestic	coef. (%)	0.050	0.165	0.117	0.066	0.078	-0.029	0.166	__0.275**__	___-0.178___	-0.066	0.011	-0.020	4.031**	__0.101**__	-0.051	0.514
		t-stat	0.730	1.705	1.258	0.724	0.853	-0.325	1.797	3.068	-1.947	-0.724	0.119	-0.213		5.383	-0.717	
	Foreign	coef. (%)	0.340	**0.116**	-0.497	-0.232	-0.163	-0.469	-0.378	***-0.617***	-0.613	-0.155	-0.081	-0.316	0.829	0.022	**0.318**	1.174
		t-stat	1.201	0.289	-1.283	-0.609	-0.430	-1.245	-0.983	-1.657	-1.616	-0.411	-0.216	-0.819		0.292	1.084	
	All Companies	coef. (%)	0.322	**0.119**	-0.462	-0.213	-0.148	-0.446	-0.347	-0.564	***-0.586***	-0.149	-0.074	-0.273	0.826	0.029	**0.294**	1.126
		t-stat	1.207	0.315	-1.263	-0.592	-0.416	-1.254	-0.957	-1.605	-1.637	-0.419	-0.208	-0.749		0.397	1.061	
BRVM	BRVM-10	coef. (%)	___-0.305*___	0.168	0.298	0.294	0.668**	0.278	-0.106	0.082	0.351*	0.329*	0.199	__0.670**__	3.772**	**-0.004**	-0.301*	5.269*
		t-stat	-2.461	0.944	1.724	1.662	3.785	1.571	-0.607	0.468	2.044	1.986	1.194	4.048		-0.096	-2.295	
	BRVM-Comp	coef. (%)	___-0.255**___	0.088	0.217	0.238	0.452**	0.185	-0.109	0.061	0.309*	0.255*	0.153	__0.618**__	5.627**	**-0.022**	-0.233*	6.221*
		t-stat	-2.926	0.699	1.786	1.911	3.638	1.488	-0.888	0.495	2.553	2.191	1.304	5.307		-0.835	-2.494	
Egypt	HFI	coef. (%)	__0.322**__	-0.428*	-0.465**	-0.423*	-0.465**	___-0.582**___	-0.565**	-0.302	-0.333*	-0.355*	-0.309	-0.220	1.789	-0.080*	__0.402**__	10.429**
		t-stat	2.699	-2.514	-2.765	-2.449	-2.775	-3.481	-3.351	-1.825	-2.002	-2.132	-1.853	-1.318		-2.251	3.229	
	EFGI	coef. (%)	__0.274*__	-0.380*	-0.415*	-0.329	-0.402*	-0.495**	___-0.508**___	-0.318	-0.323	-0.360*	-0.204	-0.128	1.378	-0.076*	__0.350**__	6.992**
		t-stat	2.159	-2.101	-2.319	-1.795	-2.258	-2.783	-2.836	-1.809	-1.829	-2.035	-1.153	-0.719		-2.012	2.644	
Ghana	GSE Index	coef. (%)	0.218	0.017	0.328	__0.570*__	-0.411	-0.140	-0.001	-0.317	***-0.417***	-0.293	-0.232	-0.025	3.624**	0.126**	**0.092**	0.305
		t-stat	1.387	0.074	1.480	2.555	-1.884	-0.633	-0.006	-1.455	-1.898	-1.342	-1.059	-0.110		2.642	0.553	
Mauritius	SEMDEX	coef. (%)	__0.113**__	-0.116	-0.134*	-0.106	___-0.160**___	-0.042	-0.111	-0.120*	-0.149*	-0.145*	-0.088	-0.072	1.273	0.000	__0.113*__	6.424*
		t-stat	2.635	-1.882	-2.255	-1.799	-2.717	-0.722	-1.908	-2.037	-2.518	-2.478	-1.484	-1.240		0.005	2.535	
	SEMTRI	coef. (%)	__0.125**__	-0.128*	-0.115	-0.054	-0.142*	-0.027	-0.089	-0.131*	___-0.146*___	-0.130*	-0.076	-0.027	1.551	0.029*	__0.096*__	4.661*
		t-stat	2.936	-2.076	-1.944	-0.921	-2.425	-0.463	-1.533	-2.242	-2.466	-2.224	-1.284	-0.457		2.404	2.159	
Morocco	CFG25	coef. (%)	0.055	0.078	0.031	-0.037	-0.129	-0.049	___-0.173*___	__0.161*__	-0.173*	-0.156*	-0.061	-0.087	3.384**	-0.002	**0.057**	0.899
		t-stat	0.960	0.961	0.385	-0.458	-1.621	-0.608	-2.169	1.985	-2.173	-1.976	-0.752	-1.092		-0.124	0.948	
Namibia	Overall	coef. (%)	0.170	-0.005	-0.134	-0.045	-0.246	-0.099	-0.209	___-0.627*___	-0.410	-0.032	**0.038**	-0.011	0.974	0.008	**0.162**	0.595
		t-stat	0.846	-0.016	-0.475	-0.154	-0.843	-0.346	-0.753	-2.206	-1.443	-0.116	0.133	-0.038		0.134	0.771	
	Local	coef. (%)	-0.041	-0.080	0.020	-0.072	**0.196**	0.003	-0.069	-0.154	0.120	-0.290	***-0.201***	0.105	0.522	-0.085	**0.044**	0.047
		t-stat	-0.213	-0.291	0.075	-0.258	0.699	0.012	-0.258	-0.565	0.440	-1.085	-0.740	0.379		-1.454	0.216	
Tunisia	BVMT	coef. (%)	__0.288**__	-0.204	-0.263*	___-0.504**___	-0.180	-0.392**	-0.126	-0.206	-0.224	-0.336**	-0.287**	-0.213	2.306**	0.022	__0.266**__	8.874**
		t-stat	3.373	-1.693	-2.173	-4.161	-1.521	-3.287	-1.063	-1.735	-1.881	-2.860	-2.411	-1.782		0.877	2.979	
	TUNINDEX	coef. (%)	__0.169**__	-0.063	-0.202**	___-0.268**___	-0.144	-0.266**	-0.123	-0.129	-0.149*	-0.223**	-0.192**	-0.147*	2.201*	-0.005	__0.173**__	9.689**
		t-stat	3.166	-0.840	-2.682	-3.542	-1.946	-3.578	-1.656	-1.739	-2.008	-3.041	-2.577	-1.969		-0.288	3.113	
Zimbabwe	Industrial	coef. (%)	__0.725**__	-0.766**	-0.414	-0.750**	-0.579**	-0.260	-0.282	-0.799**	-0.688**	-0.739**	___-0.857**___	-0.623**	2.960**	0.114*	__0.611**__	13.914**
		t-stat	4.634	-3.454	-1.896	-3.340	-2.620	-1.189	-1.303	-3.612	-3.148	-3.419	-3.918	-2.777		2.449	3.730	
	Mining	coef. (%)	0.201	-0.039	0.012	-0.445	0.109	0.033	-0.209	**0.197**	0.173	-0.109	-0.187	***-0.581***	0.670	0.111	**0.090**	0.091
		t-stat	0.700	-0.095	0.030	-1.080	0.270	0.084	-0.525	0.487	0.433	-0.274	-0.467	-1.414		1.297	0.301	

Panel (a) and panel (b) present the regression results, that is, the regression coefficients, t and F statistics for the following equations, respectively:

$R_t = \beta_1 + \beta_2 Feb_t + \beta_3 Mar_t + \beta_4 Apr_t + \beta_5 May_t + ... + \beta_{12} Dec_t + \varepsilon_t$

$R_t = \alpha_0 + \alpha_1 Jan_t + e_t$

All coefficients have been presented as percentages (multiplied by 100) since most of them became almost zero after rounding to decimal 3. This could have been avoided from the outset by calculating rates of return as percentages rather than as fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold and "Bold Italic" denote the regression coefficients for the months of the year that give the highest and lowest mean daily returns, respectively. Note that in Panel (b) only the coefficients giving the highest mean daily returns have been marked in bold.

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

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In Panel (a) of Table 10.5, January seems to give significantly positive mean daily returns for Egypt's HFI and EFGI indices, Mauritius' SEMDEX and SEMTRI, Tunisia's BVMT and TUNINDEX, and for Zimbabwe's Industrial Index. Although most of the indices, except the BRVM-10, BRVM-Composite and Namibia's Local Index, have negative coefficients for the December dummy, none of them are significant, except for the TUNINDEX (at the 5% level) and Zimbabwe's Industrial Index (at the 1% level). All the indices have at least one significant coefficient, except for Botswana's FCI and ACI, Namibia's Local Index and Zimbabwe's Mining Index, suggesting the absence of the MOY effect for these indices. The BRVM's two indices exhibit a reversed 'December decline followed by January rise' pattern. The other significant coefficients for the BRVM are for the months, May, September and October, and they are all positive. Other indices exhibiting significantly positive mean daily returns in months other than January are Botswana's DCI and Morocco's CFG25 (highest in August), and the GSE Index (highest in April). For all the other indices, the significant coefficients for the months February to November are all negative.

The results described above, and those in Panel (b) of Table 10.5, suggest the presence of a significant January effect[1] in the Egyptian indices, Mauritius, Tunisia and Zimbabwe's Industrial Index. January provides the highest (but not significant) mean daily returns for Botswana's FCI and ACI, Morocco's CFG25 and Namibia's Overall and Local Indices. A significantly negative January effect is observed for the BRVM indices.

10.5.5 Week-of-the-month effect

The week-of-the-month (WOM) effect is defined by Roux and Smit (2001)[2] as a situation in which the first trading week of the month consists of the first five trading days of the month, the second and third trading weeks consist of the sixth to the tenth, and the eleventh to fifteenth, trading days of the month, respectively. All the

[1] That is, January provides the highest mean daily returns in comparison to all the other months of the year

[2] Note that for Ghana, which trades only three times a week, we define the first trading week as the first three trading days of the month, the second week as the fourth to the sixth trading day of the month, and so forth.

remaining trading days of the month are classified as week 4. To examine the WOM effect using regression analysis, the following equation is estimated:

$$R_t = \beta_1 + \sum_{i=2}^{4} \beta_i WKi_t + \varepsilon_t \qquad (10.10)$$

where the constant β_1 represent the return for week 1, β_i is the coefficient of the dummy variable that takes the value of 1 in week *i* and 0 otherwise, for *i =2, 3 and 4*. The null hypothesis is that the mean daily returns for each week are equal and zero. The results of this regression model are presented in Table 10.6.

Table 10.6: Regression results for week-of-the-month effect

Stock Exchange	Index		(C=WK1)	WK2	WK3	WK4	F-stat
Botswana	Domestic	coef. (%)	0.094*	-0.014	**0.023**	0.005	0.176
		t-stat	2.552	-0.278	0.440	0.104	
	Foreign	coef. (%)	**0.264**	-0.161	-0.270	-0.422*	1.473
		t-stat	1.752	-0.756	-1.268	-2.039	
	All Companies	coef. (%)	**0.263**	-0.161	-0.261	-0.407*	1.528
		t-stat	1.846	-0.802	-1.301	-2.083	
BRVM	BRVM-10	coef. (%)	-0.068	-0.103	0.081	**0.167**	2.731*
		t-stat	-0.946	-1.011	0.795	1.696	
	BRVM-Comp	coef. (%)	-0.087	-0.051	0.107	**0.121**	2.760*
		t-stat	-1.697	-0.704	1.485	1.714	
Egypt	HFI	coef. (%)	**0.073**	-0.038	-0.265**	-0.170	3.113*
		t-stat	1.053	-0.392	-2.700	-1.795	
	EFGI	coef. (%)	**0.093**	-0.075	-0.294**	-0.186	3.067*
		t-stat	1.263	-0.721	-2.820	-1.849	
Ghana	GSE Index	coef. (%)	0.006	**0.206**	0.099	0.191	1.073
		t-stat	0.067	1.562	0.752	1.508	
Mauritius	SEMDEX	coef. (%)	0.019	-0.043	**0.024**	-0.023	1.455
		t-stat	0.809	-1.264	0.710	-0.689	
	SEMTRI	coef. (%)	0.046	-0.037	**0.027**	-0.026	1.437
		t-stat	1.940	-1.087	0.792	-0.805	
Morocco	CFG25	coef. (%)	-0.037	**0.064**	0.048	0.047	0.690
		t-stat	-1.122	1.364	1.009	1.022	
Namibia	Overall	coef. (%)	0.045	**0.027**	-0.004	-0.110	0.278
		t-stat	0.382	0.164	-0.023	-0.674	
	Local	coef. (%)	-0.137	-0.017	**0.120**	0.119	0.440
		t-stat	-1.222	-0.107	0.752	0.759	
Tunisia	BVMT	coef. (%)	0.056	-0.014	**0.030**	-0.058	0.601
		t-stat	1.126	-0.198	0.430	-0.864	
	TUNINDEX	coef. (%)	0.005	-0.005	0.009	**0.014**	0.076
		t-stat	0.147	-0.106	0.194	0.325	
Zimbabwe	Industrial	coef. (%)	**0.199***	-0.021	-0.118	-0.007	0.365
		t-stat	2.171	-0.164	-0.908	-0.052	
	Mining	coef. (%)	0.222	-0.147	-0.295	**0.008**	0.763
		t-stat	1.329	-0.622	-1.249	0.037	

The table present the regression results, that is, the regression coefficients, t and F statistics for the equation:

$$R_t = \beta_1 + \sum_{i=2}^{4} \beta_i WKi_t + \varepsilon_t$$

All coefficients have been presented as percentages (multiplied by 100) since most of them became almost zero after rounding to decimal 3. This could have been avoided from the outset by calculating rates of return as percentages rather than as fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold denotes the regression coefficient for the week of the month that give the highest mean daily return.

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

The results in Table 10.6 suggest that there is no strong week-of-the-month effect on the African markets studied. The only significant coefficients observed are the week 1 mean daily returns for Botswana's DCI and Zimbabwe's Industrial index (positive at the 5% level), the week 3 mean daily returns for Egypt's HFI and EFGI, and the week 4 mean daily returns for Botswana's FCI and ACI (negative at the 1% and 5% levels, respectively). Although not significant, week 1 provides the largest mean daily returns for Botswana's FCI and ACI, Egypt's HFI and EFGI, and Zimbabwe's Industrial Index. The mean daily returns are highest in week 2 for the GSE Index, the CFG25, and Namibia's Overall Index, and in week 3 for Botswana's DCI, Mauritius's SEMTRI and SEMDEX, Namibia's Local Index, and Tunisia's BVMT. The mean daily returns are highest in week 4 for both of the BRVM indices, the TUNINDEX and Zimbabwe's Mining Index. Considering the F-statistic, only the BRVM and Egypt have significant WOM effects.

10.6 Kruskal-Wallis and chi-square median tests

To give weight to the regression results above, the more robust Kruskal-Wallis and chi-square median tests are also used, and the results are also presented in Table 10.7. The Kruskal-Wallis and median tests for the TOM and TOY effects emulate those for the regression equations that make use of only one dummy explanatory variable.

The results (as shown in Table 10.7) suggest a significant DOW effect for Botswana's FCI and ACI, Morocco's CFG25 and Zimbabwe's Industrial index, using the Kruskal-Wallis test. In addition to these indices, Egypt's HFI and EFGI also exhibit significant DOW effects, using the Chi-Square Median test. Significant TOM effects are only observed on Egypt's HFI and EFGI, using the Kruskal-Wallis test, and only on the EFGI, using the Chi-square Median test. When the TOY effect is extracted from the return series, the TOM effect observed in the Egyptian indices disappears. This tends to indicate that the observed TOM effect is in actual fact a TOY effect. The two Egyptian indices are also the only indices with significant WOM effects, observed using the Kruskal-Wallis but not with the Chi-square Median test.

Table 10.7: Nonparametric Kruskal-Wallis ANOVA and median# tests results for seasonal effects

Stock Market	Stock Index	Day-of-the-week		Turn-of-the-month		Turn-of-the-month2		Turn-of-the-year		Month-of-the-year		Week-of-the-month	
		Kruskal Wallis H	Chi-Square	Kruskal Wallis H	Chi-Square	Kruskal Wallis H	Chi-Square	Kruskal Wallis H	Chi-Square	Kruskal Wallis H	Chi-Square	Kruskal Wallis H	Chi-Square
Botswana	Domestic	2.222	1.457	0.003	0.258	0.001	0.677	0.084	0.899	35.213**	27.618**	2.243	5.366
	Foreign	46.002**	66.984**	2.526	0.905	3.297	1.806	0.335	1.340	7.258	10.172	1.475	1.423
	All Companies	43.005**	31.402**	2.164	1.039	2.561	1.822	0.080	0.914	9.859	10.902	0.985	0.317
BRVM	BRVM-10	4.272	4.200	0.621	0.527	0.744	0.743	0.026	0.114	47.071**	33.517**	4.352	5.556
	BRVM-Comp	1.584	0.594	0.932	1.161	0.630	0.501	0.295	1.225	60.733**	46.796**	4.162	2.211
Egypt	HFI	6.576	13.079*	6.302*	2.523	1.852	0.151	13.160**	13.635**	18.054	16.548	11.359**	4.882
	EFGI	7.606	16.928**	7.357**	5.933*	3.239	2.284	8.677**	8.731**	16.614	17.275	11.020*	7.689
Ghana	GSE Index	n/a	n/a	0.118	0.721	0.037	0.502	0.186	0.178	40.036**	26.115**	0.734	2.605
Mauritius	SEMDEX	4.297	4.006	2.812	1.692	1.308	0.415	3.007	4.277*	18.793	14.449	5.039	7.297
	SEMTRI	4.149	2.560	2.820	1.692	1.043	0.593	4.435*	2.865	18.636	13.397	3.627	4.431
Morocco	CFG25	22.409**	23.096**	0.122	0.463	0.021	0.263	0.411	0.321	41.920**	29.347**	1.145	2.847
Namibia	Overall	7.607	8.780	0.535	0.562	0.628	0.510	0.014	0.030	12.535	10.514	2.915	5.498
	Local	2.149	5.787	2.311	1.036	1.671	0.788	0.667	0.232	9.026	12.563	5.099	1.811
Tunisia	BVMT	3.444	4.749	0.026	0.007	0.059	0.007	0.055	0.000	24.531*	17.955	0.187	0.671
	TUNINDEX	4.439	3.819	0.171	0.030	0.032	0.098	0.550	0.162	17.369	11.000	1.111	2.295
Zimbabwe	Industrial	12.303*	12.319*	0.257	0.851	0.201	0.000	8.524**	7.932**	30.448**	21.148*	0.719	1.237
	Mining	0.840	2.403	0.142	0.316	0.007	0.078	2.009	0.813	15.694	24.123*	1.966	2.018

The Median test statistic in the table is labelled "Chi-square"
** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively
Source: Chipo Mlambo (2004), University of Stellenbosch Business School

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Interestingly, even with such robust tests, the TOY and the MOY effects persist on some indices. A significant TOY effect is observed on Egypt's HFI and EFGI, and on Zimbabwe's Industrial index using both nonparametric tests. The TOY effect is also observed on Mauritius' SEMTRI and SEMDEX using the Kruskal-Wallis and the Chi-square Median tests, respectively. The relatively more persistent seasonality is the MOY effect. This is observed on Botswana's DCI, the BRVM-10 and the BRVM-Composite, the GSE Index, the CFG25 and Zimbabwe's Industrial Index, using both nonparametric tests, and on Tunisia's BVMT and Zimbabwe's Mining Index, using the Kruskal-Wallis and Chi-square Median tests, respectively.

10.6.1 SUMMARY OF FINDINGS

Table 10.8: Day/period giving highest or lowest returns from regression analysis

Description	Day	Significant	Not significant
Day-of-Week Effect *Day giving the lowest mean daily returns*	**Mon**	Botswana2	Botswana3, Zimbabwe1, Zimbabwe2
	Tues	-	Mauritius2, Morocco, Namibia2, Tunisia1, Tunisia2
	Wed	-	Egypt1, Egypt2
	Thurs	-	Botswana1, BRVM1, BRVM2, Mauritius1, Namibia1
	Fri	-	-
Day giving the highest mean daily returns	**Mon**	-	BRVM2
	Tues	-	BRVM1
	Wed	-	Botswana1, Namibia1, Namibia2, Tunisia1, Zimbabwe1
	Thurs	Morocco	Tunisia2
	Fri	Botswana2, Botswana3	Egypt1, Egypt2, Mauritius1, Mauritius2, Zimbabwe2
Monday/ Weekend Effect *Day giving the lowest mean daily returns*	**Mon**	Botswana2, Botswana3, Morocco	Botswana1, BRVM1, Egypt1, Egypt2, Mauritius1, Mauritius2, Namibia1, Tunisia1, Zimbabwe1, Zimbabwe2
	ROW	-	BRVM2, Namibia2, Tunisia2
End/ Turn-of-the-Month Effect *Days giving the highest mean daily returns*	**EOMN1**	-	BRVM1, BRVM2, Ghana
	EOMP1	-	Botswana1, Tunisia1, Tunisia2
	EOMP2	Botswana2, Botswana3	Zimbabwe1
	EOMP3		Morocco, Namibia2, Zimbabwe2
	EOMP4	Mauritius2	Egypt1, Egypt2, Mauritius1, Namibia1
	ODM	-	-
Turn-of-Month Effect *Period giving the highest mean daily returns*	**TOM**	Botswana2, Botswana3, Egypt1, Egypt2, Mauritius1, Mauritius2	Botswana1, Namibia1, Namibia2, Tunisia2, Zimbabwe1, Zimbabwe2
	ROM	Ghana	BRVM1, BRVM2, Morocco, Tunisia1
Turn-of-Month Effect* *Period giving the highest mean daily returns*	**TOM***	Botswana2, Botswana3,	Botswana1, Egypt1, Egypt2, Mauritius1, Mauritius2, Namibia1, Namibia2
	ROM*	Ghana, Zimbabwe1	BRVM1, BRVM2, Morocco, Tunisia1, Tunisia2, Zimbabwe2
End/ Turn-of-the-Year Effect *Days giving the highest mean daily returns*	**JANN1**	BRVM1, BRVM2, Zimbabwe2	Botswana1, Ghana, Namibia1
	JANP1	Egypt1, Egypt2	-
	JANP2	-	Zimbabwe1
	JANP3	Namibia2	Morocco

Description	Day	Significant	Not significant
	JANP4	-	Botswana2, Botswana3, Mauritius1, Mauritius2, Tunisia1, Tunisia2
	ODY	-	-
Turn-of-Year Effect *Period giving the highest mean daily returns*	TOY	Egypt1, Egypt2, Zimbabwe1	Botswana2, Botswana3, BRVM1, BRVM2, Ghana, Mauritius1, Mauritius2, Namibia2, Tunisia2, Zimbabwe2
	ROY	Botswana1	Morocco, Namibia1, Tunisia1
Month-of-Year/ January Effect *Month giving the highest mean daily returns*	Jan	Egypt1, Egypt2, Mauritius1, Mauritius2, Tunisia1, Tunisia2, Zimbabwe1	-
	Feb	-	Botswana2, Botswana3
	Mar	-	-
	Apr	Ghana	-
	May	-	Namibia2
	Jun	-	-
	Jul	-	-
	Aug	Botswana1, Morocco	Zimbabwe2
	Sep	-	-
	Oct	-	-
	Nov	-	Namibia1
	Dec	BRVM1, BRVM2	-
Month giving the lowest mean daily returns	Jan	BRVM1, BRVM2	-
	Feb	-	-
	Mar	-	-
	Apr	Tunisia1, Tunisia2	-
	May	Mauritius1	-
	Jun	Egypt1	-
	Jul	Egypt2, Morocco	-
	Aug	Namibia1	Botswana2
	Sep	Mauritius2	Botswana1, Botswana3, Ghana
	Oct	-	-
	Nov	Zimbabwe1	Namibia2
	Dec	-	Zimbabwe2
January Effect *Month giving the highest mean daily returns*	Jan	Egypt1, Egypt2, Mauritius1, Mauritius2, Tunisia1, Tunisia2, Zimbabwe1	Botswana2, Botswana3, Ghana, Morocco, Namibia1, Namibia2, Zimbabwe2
	OMY	Botswana1	BRVM1, BRVM2
Week-of-the-month Effect *Week giving the highest mean daily returns*	Wk 1	Zimbabwe1	Botswana2, Botswana3, Egypt1, Egypt2,
	Wk 2	-	Ghana, Morocco, Namibia1
	Wk 3	-	Botswana1, Mauritius1, Mauritius2, Namibia2, Tunisia1
	Wk 4	-	BRVM1, BRVM2, Tunisia2, Mining

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

Table 10.9: Significant effects (at the 5% level) using the Kruskal-Wallis and median tests

Effect	Kruskal-Wallis	Chi-square
Day-of-week	Botswana2, Botswana3, Morocco, Zimbabwe1	Botswana2, Botswana3, Egypt1, Egypt2, Morocco, Zimbabwe1
Turn-of-the-month	Eypt1, Egypt2	Egypt2
Turn-of-the-month*	-	-
Turn-of-the-year	Egypt1, Egypt2, Mauritius2, Zimbabwe1	Egypt1, Egypt2, Mauritius1, Zimbabwe1
Month-of-the-year	Botswana1, BRVM1, BRVM2, Ghana, Morocco, Tunisia1, Zimbabwe1	Botswana1, BRVM1, BRVM2, Ghana, Morocco, Zimbabwe1, Zimbabwe2
January		
Week-of-the-month	Egypt1, Egypt2	-

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

Key to Tables 10.8 and 10.9 : Botswana1=Domestic Companies Index, Botswana2=Foreign Companies Index, Botswana3= All Companies Index, BRVM1=BRVM-10 Index, BRVM2=BRVM-Composite Index, Egypt1=Hermes Financial Index, Egypt2=EFGI, Ghana=Ghana stock Exchange Index, Mauritius1=SEMDEX, Mauritius2=SEMTRI, Morocco=CFG25, Namibia1=Overall Index, Namibia2=Local Index, Tunisia1=BVMT, Tunisia2=TUNINDEX, Zimbabwe1=Industrial Index, Zimbabwe2=Mining Index

* After removing the turn-of-the-year effect

10.7 Summary and concluding remarks

Stock market seasonal effects on seventeen indices from nine African stock markets are examined. Using regression analysis, significant Monday effects were found on two of Botswana's indices, the FCI and the ACI, and on Morocco's CFG25. Significant turn-of-the-month effects were found on the FCI and ACI, and on the Egyptian and Mauritius indices, using regression analysis. The turn-of-the-month effects disappeared for Egypt and Mauritius after removing the turn-of-the-year effects, suggesting that the turn-of-the-month effects on these markets could be turn-of-the-year effects. However, the turn-of-the-year effects were significant only for Egypt and Zimbabwe's Industrial Index, but not for Mauritius. Significant month-of-the-year effects were observed on the BRVM, Morocco, Tunisia, Ghana, Botswana's Domestic Companies Index and Zimbabwe's Industrial Index. A reversed December/January pattern was observed for the BRVM to indicate the highest mean daily returns in December and the lowest mean daily returns in January. For Egypt, Mauritius, Tunisia and Zimbabwe's Industrial Index, January provided the highest, significantly positive mean daily returns as compared to all the other months of the year. Significant week-of-the-month effects were evident only for the BRVM and Egyptian indices.

The seasonal effects were almost just as strong using the nonparametric Kruskal-Wallis and Chi-square Median tests for all except the turn-of-the-month and week-of-the-month effects in which the effects were only significant for the Egyptian indices. In addition to the markets exhibiting significant effects under the regression analysis method, Egypt and Zimbabwe's Industrial Index also exhibited significant day-of-the-week effects using the Chi-square Median test. Significant turn-of-the-year effects were also observed on Mauritius' SEMDEX and SEMTRI using the Chi-square Median and Kruskal-Wallis tests respectively. The month-of-the-year effects observed under regression analysis were confirmed on most indices using the Kruskal-Wallis test.

While the indices for most markets exhibited at least one seasonal effect, no significant seasonal effects were observed for the Namibian indices using the nonparametric tests, providing further support that this market is weak-form efficient.

On the other markets, the presence of these predictable seasonal patterns seems to suggest exploitable opportunities for abnormal gains.

The possible explanations for these seasonal effects, the month-of-the-year effect in particular, could be seasonal information flows, the financial reporting and dividend distribution dates, and window dressing by institutional investors. For example, the day-of-the-week effect on Zimbabwe's Mining Index (although weak), as observed from regression analysis, could be a spill over effect due to the stocks constituting this index. Some of these stocks are foreign/multinational corporations, which tend to be affected not only by local events, but also world trends and events in their home countries. The same is true for the dual-listed stocks on some markets, for example the Ashanti Goldfields Corporation in Ghana, which constitute more that 75 percent of the market capitalisation of shares listed on the GSE. Therefore some of the seasonal effects observed may be indirectly spill over effects from overseas markets.

Most indices in this study exhibit the highest mean daily returns in January. The explanations cited in the literature for the January effect seems to apply on these African markets as well, considering the fact that most of the stocks listed on these African stock exchanges are mostly small firms. However, finding explanations as to why these seasonal effects exist on the African markets is not the intention of this study, although it will be interesting for future research.

11 BENCHMARKING ANALYSIS: STOCK MARKET SEASONAL EFFECTS

11.1 Introduction

Recent research on the EMH focuses more on discovering patterns that contradict the hypothesis. This is known as the 'anomalies literature'. According to Frankfurter and McGoun (2001), the word 'anomaly' in finance refers to studies that show evidence contrary to the empirical validity of the EMH of Fama (1965, 1970) and/or the CAPM of Black (1972), Lintner (1965), Sharpe (1964) and others. According to Madureira and Leal (2001), while the random walk model describes the behaviour of the market and implies its weak form efficiency, many well-known patterns have defied this theory. The existence of seasonal patterns in capital markets, for example, has been taken to suggest some degree of market inefficiency, in that these seasonal patterns can possibly be exploited for abnormal gains.

The investigation in Chapter 10 indicates the existence of some seasonal patterns on African stock markets. However, the investigation of seasonal patterns in isolation is less interesting. It is vital to benchmark such results with those obtained on stock markets in other parts of the world to find out if the observed seasonal effects are a global phenomenon or not. According to Brusa, *et al.* (2003), earlier studies suggest that the weekend effect is not an isolated anomaly but rather a worldwide phenomenon observed both in the United States and in foreign countries.

One interesting hypothesis is the fact that the Monday effect on the U.S. market has been found to occur on a Tuesday on other markets outside the U.S. (see for example, Jaffe and Westerfield (1985) for Japan and Australia; Kim (1988) for Korea, Japan and Australia; Aggarwal and Rivoli (1989) for Hong Kong, Singapore, Malaysia and the Philippines; Ziemba (1993) for the Japanese stock market; and Dubois and Louvet (1996) for other markets around the world). One explanation given for this pattern is referred to as the time zone/lag hypothesis in which the influence of the U.S. market is believed to disguise the indigenous weekend effect in those markets which close before it opens (Condoyanni, *et al.*, 1987).

Fatemi and Park (1996) investigated regularities in the Japanese American Depository Receipts (ADRs) returns in comparison to their underlying securities. They found that the patterns of returns of Japanese ADRs are affected by their trading in the US market. To that effect, Monday average returns were found to be significantly lower on ADRs than on their underlying securities. The reverse was found to be the case on Tuesdays when average returns were found to be lower on the underlying securities than on the ADRs. These findings suggest that the pattern of returns on securities tend to depend on the market in which they trade, rather than fundamentals on the underlying assets.

Most of the explanations given as to why some seasonal effects exist tend to be market specific. In the event that the same seasonal effect is observed on another market, with probably different characteristics to the former, then the question that arises is what else causes such seasonal effect, if the explanation for one market is not relevant for the other. For example, while the tax-loss selling hypothesis has been an applauded explanation for the January effect on those markets with the December tax-year end, it however, does not apply on markets where the tax-years end in months other than December.

Gu (2003) suggested that his findings of a declining January effect on the U.S. market could be an indication that the factors explaining the effect, or their impacts, are changing. He also suggested that the declining January effect might represent a trend towards market efficiency. According to him, more experienced and knowledgeable investors, and advances in information technology (such as greater quantity, better quality, and lower cost of information, and faster communication and order execution) should make the markets more efficient. On the basis of this argument, Gu (2003) suggested that developed markets are, in fact, more efficient than less developed and emerging markets and that this might act as an encouragement to believers of the efficient markets theory.

In this chapter, seasonal effects on stock markets in other regions are examined and comparisons made with the results on African stock markets studied in the previous chapter. This will shed more light on whether these seasonal patterns are not unique to specific markets, but are rather a global phenomenon.

11.2 Data and methodology

Daily indices data were obtained from Reuters and validated with that obtained from DataStream for overlapping periods. The periods of investigation are from 14 July 1994 to 13 July 2004 for Australia, Brazil, Finland, Malaysia, New Zealand and Poland, 1 March 1999 to 13 July 2004 for Slovenia, 30 June 1995 to 13 July 2004 for South Africa[1], and 2 January 1990 to 30 June 2004 for the United States. Although the benchmarks were chosen according to regional location and popularity, for Eastern Europe, two markets were included, Poland and Slovenia. While for Slovenia the period is rather short, for Poland it is similar to that for most other markets in the sample. The reason for including Slovenia is that this market is relatively new and not as widely researched compared to the other benchmarks. Slovenia is, therefore, expected to compare well with the African markets in the previous chapter. Table 11.1 below presents these markets, the regions where they are located, the indices used and the periods covered for each of these markets.

Table 11.1:General information

Region	Country	Stock Exchange	Stock Index	Period covered
Australia	Australia	Australian Stock Exchange	All Ordinaries Share Index	14-Jul-94 to 13-Jul-04
Latin America	Brazil	Sao Paulo Stock Exchange	BOVESPA	14-Jul-94 to 13-Jul-04
Western Europe	Finland	Helsinki Stock Exchange	HEX Index	14-Jul-94 to 13-Jul-04
Asia	Malaysia	Kuala Lumpur Stock Exchange	KLSE Composite	14-Jul-94 to 13-Jul-04
Island	New Zealand	New Zealand Exchange Ltd	NZ Composite	14-Jul-94 to 13-Jul-04
Eastern Europe	Poland	Warsaw Stock Exchange	Warsaw General Index	14-Jul-94 to 13-Jul-04
Eastern Europe	Slovenia	Ljubljana Stock Exchange	Ljubljana Index	01-Mar-99 to 13-Jul-04
Africa	South Africa	Johannesburg Stock Exchange	JSE All Share index	30-Jun-95 to 13-Jul-04
North America	United States	New York Stock Exchange	NYSE Composite	02-Jan-90 to 30-Jun-04

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

[1] Note that the Johannesburg Stock Exchange is also included as a benchmark, upon which the African stock markets in the previous chapter are compared.

The number of data points and other descriptive statistics for the markets are presented in Table 11.2. The table shows that the markets have positive mean returns except for Malaysia. Kunkel, *et al.* (2003) also found a negative mean return for Malaysia and attributed it largely to the 51 percent decline in the Kuala Lumpur Composite Index in 1997 when Malaysia was the hardest hit of all Asian countries during the Asian financial turmoil.

The returns are also skewed and have excess kurtosis. This is particularly so for the U.S. market with a skewness of 55.86 and a kurtosis of 3289.57. The Kolmogorov-Smirnov test statistics also suggest deviations from normality at the 1% level of significance for all the nine indices for the nine benchmarking countries. This is similar to what was observed for the indices on the African stock markets in the previous chapter. Therefore, the distribution of returns for the African markets is similar to that for the JSE and markets in other regions.

Table 11.2: Descriptive statistics for stock index returns

Country	Obs.	Mean (%)	Std. Dev. (%)	Skewness	Std. Err.	Kurtosis	Std. Err.	K-S d-stat
Australia	2530	0.023	0.792	-0.4859	0.0487	5.957	0.0973	0.0391**
Brazil	2475	0.068	2.591	0.5379	0.0492	12.140	0.0984	0.0627**
Finland	2498	0.047	2.178	-0.4381	0.0490	5.833	0.0979	0.0655**
Malaysia	2462	-0.007	1.765	0.5626	0.0493	37.046	0.0986	0.1168**
New Zealand	2510	0.010	0.857	-1.1603	0.0489	27.757	0.0977	0.0635**
Poland	2484	0.033	1.785	-0.1735	0.0491	3.129	0.0982	0.0621**
Slovenia	1312	0.101	0.993	0.3918	0.0675	7.668	0.1350	0.0906**
South Africa	2256	0.032	1.221	-0.8112	0.0515	9.217	0.1030	0.0629**
United States	3655	0.096	4.053	55.8624	0.0405	3289.571	0.0810	0.3200**

** Implies significance at the 5% level

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

The methodology used is regression on dummy variables and the Kruskal-Wallis and median tests as in Chapter 10. Therefore, the regression equations are not repeated here.

11.3 Empirical results

11.3.1 Day-of-the-week effect

The results in Panel (a) of Table 11.3 indicate that Mondays provide the lowest mean daily returns for Brazil, Malaysia and New Zealand. However, these negative Monday mean daily returns are significant only for Malaysia and New Zealand. While the Monday effect is not significant for Brazil, other researchers (e.g. Agrawal and Tandon, 1994) found returns to be significantly lower on Mondays in Brazil. These negative returns on Mondays for Brazil, have been hypothesised to follow a decline in the market during the prior week and that they disappear when the market rises in the previous weeks, a pattern referred to as the twist-of-the-Monday effect (Madureira and Leal, 2001). The twist-of-the-Monday effect for Brazilian indices was also found by Aggarwal and Leal (1996) and Agrawal and Tandon (1994). Madureira and Leal (2001) suggest that the twist-of-the-Monday effect is due to index construction problems, such as the nonsynchronous trading of stocks, as it is evident only in indices and not individual stock returns.

Chang, *et al.* (1998) also found the Monday returns on the U.S. markets to be related to returns in the previous week. They found that on the U.S. market, the seasonal in the arrival of negative news on Mondays is somewhat offset by a seasonal in the arrival of positive news on Fridays. The asymmetric lagged response to negative news that arrives on Friday was found to be less pervasive than the asymmetric concurrent response to negative news that arrives on Monday. Returns on smaller stocks were found to more closely mimic returns on large stocks on Mondays than on other weekdays because large firm stock returns are extra-informative to small investors on Mondays. Dubois and Louvet (1996) also suggest that the low trading volumes on Mondays suggest that institutional investors are less active on this day.

While prior studies for the US markets suggest the lowest mean daily returns on Mondays, in the current study, the New York Stock Exchange Composite Index's mean daily returns are lowest (but not significant at the 5% level) on a Friday. This finding is, however, somehow consistent with the "reverse" weekend effect observed by Brusa, *et al.* (2000) and Brusa, *et al.* (2003). Brusa, *et al.* (2003) found the reverse weekend effect to be unique to the U.S. stock market, while the traditional weekend effect either persist or is nonexistent on foreign markets. Chang, *et al.* (1993) and Dubois and Louvet (1996) also reported that the weekend effect has recently disappeared for the U.S., while Agrawal and Tandon (1994) pointed out several U.S. studies indicating that the Monday effects seem to have recently disappeared on the U.S. markets.

Table 11.3: Regression results for day-of-the-week/Monday effect

			(a)						(b)		
Country	**Index**		(C=Mon)	Tue	Wed	Thu	Fri	F-stat	(C=ROW)	Mon	F-stat
Australia	Ordinary	coef. (%)	0.012	-0.003	**0.047**	0.021	***-0.010***	0.430	0.026	***-0.014***	0.118
		t-stat	0.329	-0.069	0.929	0.417	-0.191		1.457	-0.344	
Brazil	BOVESPA	coef. (%)	***-0.159***	0.347*	0.289	0.031	**0.467******	3.054*	0.125*	***-0.284****	4.781*
		t-stat	-1.372	2.114	1.759	0.188	2.839		2.149	-2.187	
Finland	HEX Index	coef. (%)	0.101	-0.184	***-0.245***	0.044	**0.127**	2.617*	***0.034***	0.067	0.379
		t-stat	1.038	-1.345	-1.789	0.321	0.920		0.698	0.616	
Malaysia	KLSE Index	coef. (%)	***-0.192****	0.191	0.277*	0.164	0.285*	2.071	0.038	***-0.230****	6.518*
		t-stat	-2.378	1.691	2.449	1.448	2.525		0.948	-2.553	
New Zealand	NZ Composite	coef. (%)	***-0.083****	0.089	0.117*	0.098	**0.158******	2.244	0.033	***-0.115******	7.057**
		t-stat	-2.119	1.635	2.158	1.792	2.886		1.715	-2.656	
Poland	General	coef. (%)	**0.159***	-0.247*	***-0.261****	-0.033	-0.081	2.343	***0.002***	0.157	3.079
		t-stat	1.981	-2.193	-2.317	-0.292	-0.708		0.038	1.755	
South Africa	All Share Index	coef. (%)	**0.097**	-0.040	***-0.100***	-0.089	-0.094	0.559	***0.016***	0.081	1.544
		t-stat	1.658	-0.491	-1.220	-1.094	-1.146		0.556	1.243	
Slovenia	Ljubljana	coef. (%)	0.042	***-0.070***	0.001	0.127	**0.238******	4.042**	0.116**	***-0.074***	1.174
		t-stat	0.690	-0.810	0.014	1.478	2.762		3.793	-1.084	
United States	NYSE Composite	coef. (%)	0.061	-0.031	-0.028	**0.270**	***-0.038***	0.780	0.104	***-0.043***	0.063
		t-stat	0.399	-0.143	-0.129	1.258	-0.175		1.397	-0.252	

Panel (a) and panel (b) present the regression results, that is, the regression coefficients, t and F statistics for the following equations, respectively:

$R_t = \beta_1 + \beta_2 Tue_t + \beta_3 Wed_t + \beta_4 Thu_t + \beta_5 Fri_t + \varepsilon_t$

$R_t = \alpha_0 + \alpha_1 Mon_t + e_t$

All coefficients have been presented as percentages (multiplied by 100) since most of them become almost zero after rounding to decimal 3. This could be avoided from the outset by calculating rates of return as percentages rather than as simple fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold and "***Bold Italic***" denote the regression coefficients for the days of the week that give the highest and lowest mean daily returns, respectively. Note that in Panel (b) only the coefficients that give the lowest mean daily returns have been marked in bold italic.

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

The Tuesday effect hypothesised for the Australian and other Asian markets is not evident in the current study. None of the markets provided the lowest mean daily returns on a Tuesday except for Slovenia. However, this Tuesday effect for Slovenia is not significant. On the African markets studied in the previous chapter, five indices, Mauritius' SEMTRI, Morocco's CFG25, Namibia's Local Index and Tunisia's BVMT and TUNINDEX, exhibited a similar pattern (that is, the lowest, although not significant, mean daily returns on a Tuesday).

The mean daily returns are lowest on a Wednesday for Finland, Poland and South Africa. For the African stock markets in the previous chapter, only the Egyptian indices exhibited the lowest mean daily returns on a Wednesday, but these were not significant. For the benchmarking markets, only Poland has significant lowest mean daily returns on a Wednesday.

The literature has also indicated evidence that the highest mean daily returns occur on a Friday. This was also evident in this study for Brazil, Malaysia, New Zealand and Slovenia (significant at the 5% level) and Finland (insignificant). For the US market, where the highest mean daily returns on a Friday were first hypothesised, they are observed to occur on a Thursday in this study. This is, however, different from the findings in Brusa, *et al.* (2003) where the highest returns were observed on Monday, and thus a reverse weekend effect. Mookerjee and Yu (1999) also documented the highest mean daily returns to occur on a Thursday rather than on a Friday, on the Shanghai and Shenzhen stock exchanges in China.

In the previous chapter, Morocco's CFG25 and Tunisia's TUNINDEX also gave the highest mean daily returns on a Thursday. Botswana's FCI and ACI were consistent with the results for Brazil, Malaysia, New Zealand and Slovenia, exhibiting the highest mean daily returns, which are significant, on a Friday. The Egyptian and Mauritius indices, and Zimbabwe's Mining Index also exhibited the highest (but not significant) mean daily return on a Friday. The highest returns for Poland and South Africa are on a Monday, consistent with the BRVM-Composite. None of the benchmarking indices exhibited the highest mean daily returns on a Wednesday whereas for the African stock markets in Chapter 10, the Namibian indices, Tunisia's BVMT, Zimbabwe's Industrial Index and Botswana's DCI exhibited the highest mean daily returns on a Wednesday.

When comparing Monday with the rest of the week, the Monday effect was evident for six of the nine benchmarking indices. However, it was only significant for Brazil, Malaysia and New Zealand. For Finland, Poland and South Africa, no Monday effect was found to exist. The results are similar to those obtained for the African indices, where all the indices, except the BRVM composite, Namibia's Local Index and the TUNINDEX, exhibited a Monday effect.

11.3.2 End/turn-of-the-month effect

The benchmarking indices exhibit the highest mean daily returns on any one of the TOM days. The highest mean daily return is on the last day of the month for Finland, similar to the results for the BRVM indices and Ghana (although these were not significant), on the first day of the month for South Africa and the US similar to Botswana's DCI and Tunisia (which were however not significant), on the second day of the month for Australia, Brazil and New Zealand, similar to Botswana's FCI and ACI, on the third day for Slovenia, similar to Morocco's CFG25, Namibia's Local Index and Zimbabwe's Mining Index, (although for these African markets, the returns are not significant), on the fourth day of the month for Malaysia and Poland, similar to the Egyptian and Mauritius indices, and Namibia's Overall Index. These results are presented in Table 11.4.

Panels (b) and (c) show that the TOM days combined give the highest mean daily returns for all the benchmark indices. This is reflected by the positive coefficients on the TOM dummy variable. In addition, in every country, the mean returns during the TOM period are greater than the mean returns during the ROM period. The t-statistics show that in 6 countries these returns are significant. Similar evidence for Australia, Brazil, Malaysia, New Zealand, South Africa and the U.S. was found by Kunkel, *et al.* (2003) although their TOM definition was slightly different from that used in this study.

After controlling for the TOY effect, the mean returns for TOM period dropped for all countries except Malaysia. The TOM was still significant at the 1% level for South Africa but became weaker for Australia and Finland, while it became insignificant for New Zealand, Poland and the US. The same was observed for Egypt and Mauritius. Boudreaux (1995) found average returns to be highest in the last days of the month for Singapore/Malaysia (a reverse effect). Even after extracting the first trading days in January, Singapore/Malaysia continued to exhibit a negative effect at the 1% level of significance.

Table 11.4: Regression results for end/turn-of-the-month effect

Country	Index		(a)							(b)			(c)		
			(C=ODM)	EOMN1	EOMP1	EOMP2	EOMP3	EOMP4	F-stat	(C=ROM)	TOM	F-stat	(C=ROM2)	TOM2	F-stat
Australia	Ordinary	coef. (%)	0.000	0.108	0.132	**0.194****	0.030	0.026	2.178	0.000	**0.098****	7.008**	0.004	**0.089***	5.427*
		t-stat	-0.018	1.457	1.773	2.600	0.402	0.345		-0.018	2.647		0.201	2.330	
Brazil	BOVESPA	coef. (%)	0.012	0.056	0.519*	**0.604***	-0.033	0.020	2.052	0.012	**0.233**	3.686	0.026	**0.188**	2.254
		t-stat	0.194	0.230	2.128	2.479	-0.136	0.083		0.194	1.920		0.446	1.501	
Finland	HEX Index	coef. (%)	-0.021	**0.540****	0.348	0.062	0.122	0.351	2.323*	-0.021	**0.285****	7.817**	-0.005	**0.237***	5.110*
		t-stat	-0.421	2.640	1.700	0.304	0.597	1.715		-0.421	2.796		-0.100	2.261	
Malaysia	KLSE Index	coef. (%)	-0.032	0.092	-0.019	0.039	0.047	**0.360***	0.991	-0.032	**0.104**	1.566	-0.036	**0.129**	2.269
		t-stat	-0.788	0.553	-0.113	0.235	0.281	2.163		-0.788	1.251		-0.884	1.506	
New Zealand	NZ Composite	coef. (%)	-0.008	0.107	-0.015	**0.231****	0.018	0.053	1.995	-0.008	**0.079***	3.853*	-0.002	**0.058**	1.938
		t-stat	-0.424	1.325	-0.190	2.873	0.217	0.657		-0.424	1.963		-0.109	1.392	
Poland	General	coef. (%)	-0.025	0.143	**0.374***	0.220	0.048	**0.419***	2.394*	-0.025	**0.241****	8.320**	-0.001	**0.152**	3.095
		t-stat	-0.618	0.854	2.231	1.310	0.288	2.497		-0.618	2.884		-0.019	1.759	
South Africa	All Share Index	coef. (%)	-0.021	0.128	**0.321****	0.281*	0.166	0.191	3.017**	-0.021	**0.218****	13.181**	-0.013	**0.201****	10.547**
		t-stat	-0.707	1.059	2.668	2.337	1.380	1.585		-0.707	3.631		-0.438	3.248	
Slovenia	Ljubljana	coef. (%)	0.082**	0.254*	-0.287*	0.035	**0.268***	0.138	2.988*	0.082**	**0.082**	1.644	0.085**	**0.073**	1.222
		t-stat	2.598	1.974	-2.234	0.271	2.101	1.080		2.589	1.282		2.738	1.105	
United States	NYSE Composite	coef. (%)	0.013	0.078	**1.613****	0.063	-0.001	0.005	5.220**	0.013	**0.350***	4.947*	0.093	**0.013**	0.007
		t-stat	0.167	0.245	5.092	0.200	-0.004	0.015		0.166	2.224		1.228	0.082	

Panel (a) and panels (b) and (c) present the regression results, that is, the regression coefficients, t and F statistics for the following equations, respectively:

$$R_t = \beta_0 + \beta_1 EOMN1_t + \sum_{i=1}^{4} \beta_{i+1} EOMPi_t + \varepsilon_t$$

$$R_t = \alpha_0 + \alpha_1 TOM_t + e_t$$

All coefficients have been presented as percentages (multiplied by 100) since most of them become almost zero after rounding to decimal 3. This could be avoided from the outset by calculating rates of return as percentages rather than as fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold denotes the regression coefficients for the days of the month that give the highest mean daily returns.

Panel (c) presents the turn-of-the-month effect after extracting the turn-of-the-year effect

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

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11.3.3 The end/turn-of-year effect

The last day of the year gives the highest mean daily returns for Malaysia, although not significant at the 5% level, as compared to six indices for the African markets in the previous chapter. The first day of the year gives the highest mean daily returns for Finland, Poland, and the US. For the African stock markets, the first day of the year also gave the highest mean daily returns for the Egyptian indices.

Table 11.5: Regression results for end/turn-of-the-year effect

Country	Index		(C=ODY)	JANN1	JANP1	JANP2	JANP3	JANP4	F-stat	(C=ROY)	TOY	F-stat
Australia	Ordinary	coef. (%)	0.020	0.081	0.244	-0.278	**0.541***	0.081	1.407	0.020	**0.134**	1.399
		t-stat	1.274	0.323	0.972	-1.108	2.156	0.324		1.273	1.183	
Brazil	BOVESPA	coef. (%)	0.058	0.719	1.027	**1.348**	0.464	-0.949	1.335	0.058	**0.522**	1.989
		t-stat	1.095	0.876	1.251	1.643	0.566	-1.156		1.094	1.410	
Finland	HEX Index	coef. (%)	0.036	0.725	**1.639***	-0.142	-0.138	0.768	1.609	0.036	**0.571**	3.367
		t-stat	0.818	1.052	2.377	-0.206	-0.200	1.113		0.818	1.835	
Malaysia	KLSE Index	coef. (%)	-0.004	0.430	-1.314*	-0.256	0.160	0.175	1.304	-0.004	-0.161	0.407
		t-stat	-0.102	0.769	-2.350	-0.457	0.287	0.312		-0.102	-0.638	
New Zealand	NZ Composite	coef. (%)	0.006	0.158	0.201	**0.488**	0.475	-0.179	1.517	0.006	**0.229**	3.492
		t-stat	0.344	0.581	0.739	1.799	1.752	-0.659		0.344	1.869	
Poland	General	coef. (%)	0.014	0.407	**1.636****	1.401*	-0.440	1.559**	4.643**	0.014	**0.913****	12.868**
		t-stat	0.401	0.722	2.903	2.486	-0.780	2.766		0.401	3.587	
South Africa	All Share Index	coef. (%)	0.026	-0.132	-0.083	-0.025	**1.048****	0.532	1.691	0.026	**0.268**	2.126
		t-stat	1.014	-0.324	-0.203	-0.062	2.571	1.305		1.014	1.458	
Slovenia	Ljubljana	coef. (%)	0.099**	0.208	-1.017*	0.138	0.552	**0.772**	2.030	0.099**	**0.131**	0.424
		t-stat	3.581	0.468	-2.289	0.310	1.242	1.738		3.573	0.651	
United States	NYSE Composite	coef. (%)	0.034	-0.076	**16.622****	0.168	0.047	-0.452	50.114**	0.034	**3.124****	42.992**
		t-stat	0.512	-0.073	15.820	0.165	0.046	-0.446		0.498	6.557	

Panel (a) and panel (b) present the regression results, that is, the regression coefficients, t and F statistics for the following equations, respectively:

$$R_t = \beta_0 + \beta_1 JANN1_t + \sum_{i=1}^{4} \beta_{i+1} JANPi_t + \varepsilon_t$$

$$R_t = \alpha_0 + \alpha_1 TOY_t + e_t$$

All coefficients have been presented as percentages (multiplied by 100) since most of them became almost zero after rounding to decimal 3. This could have been avoided from the outset by calculating rates of return as percentages rather than as fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold denotes the regression coefficients for the days of the year that give the highest mean daily returns.

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

Brazil and New Zealand have their highest mean daily returns on the second day in January, Australia and South Africa on the third day and Slovenia on the fourth day. Corresponding to the same results are Zimbabwe's Industrial Index, Morocco's CFG25 and Namibia's Local Index giving their highest returns on the second trading day in January; Botswana's FCI and ACI, Mauritius' SEMDEX and SEMTRI, giving their highest returns on the third trading day in January; and Tunisia's BVMT and TUNINDEX, giving their highest returns on the fourth trading day.

In Panel (b) of Table 11.5, there is evidence of a TOY effect, but it is only significant for Poland and the US, while no TOY effect was observed for Malaysia. For the African markets studied, the TOY effect was significant only for the Egyptian indices and Zimbabwe's Industrial index, while no TOY effect was observed for Botswana's DCI, Morocco's CFG25, Namibia's Overall Index and Tunisia's BVMT.

11.3.4 Month-of-the-year/January effect

While the coefficients for the months February to December are significantly negative for the US, the coefficient for the month of January is significantly positive. However, for the benchmark markets, the highest mean daily returns are observed in January only for the US. The January effect on the U.S. market has been observed in Rozeff and Kinney Jr. (1976). Gu (2003), however, found a declining trend in the January effect for both large and small firm indices since 1988 on the U.S. markets and report that the effect is disappearing for the Russell indices. Ariel (1987) found stocks to earn a positive average return in the first half of the calendar months and zero average returns during the second half.

Although South Africa exhibits the highest mean daily returns in December, they are not significant. Ironically, none of the markets exhibit the lowest mean daily returns in December as hypothesised in the literature. Even for the US market, the lowest mean daily returns are in August. In fact none of the markets have the lowest mean daily returns in the last three months of the year. This is shown in Table 11.6.

All the lowest mean daily returns are either in August or in September, except for Slovenia. This is comparable to the African markets where only three indices exhibited the lowest mean daily returns in the last three months of the year, Namibia's Local index and Zimbabwe's Industrial Index (November) and Zimbabwe's Mining Index (December).

Although the highest mean daily returns are concentrated in January for the African markets, the lowest mean daily returns are not prevalent in any specific month.

Table 11.6: Regression results for month-of-the-year/January effect

Country	Index		(C=Jan)	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	F-stat	(C=OMY)	Jan	F-stat
Australia	Ordinary	coef. (%)	0.027	-0.011	-0.030	**0.110**	-0.049	0.032	-0.016	-0.055	***-0.072***	-0.018	0.019	0.068	0.891	0.023	**0.004**	0.005
		t-stat	0.479	-0.141	-0.384	1.382	-0.634	0.406	-0.212	-0.713	-0.929	-0.229	0.244	0.863		1.374	0.070	
Brazil	BOVESPA	coef. (%)	0.154	-0.120	-0.059	-0.005	-0.152	-0.075	-0.147	***-0.227***	-0.198	-0.209	**0.159**	0.039	0.409	0.060	**0.093**	0.249
		t-stat	0.856	-0.456	-0.233	-0.020	-0.602	-0.295	-0.585	-0.907	-0.781	-0.829	0.619	0.151		1.106	0.499	
Finland	HEX Index	coef. (%)	0.064	-0.117	-0.033	0.166	-0.158	-0.042	-0.079	***-0.174***	-0.133	**0.189**	0.185	0.003	0.769	0.046	**0.018**	0.013
		t-stat	0.424	-0.544	-0.154	0.761	-0.735	-0.197	-0.377	-0.823	-0.627	0.897	0.871	0.015		1.008	0.116	
Malaysia	KLSE Index	coef. (%)	0.102	**0.146**	-0.164	-0.182	-0.111	-0.181	-0.154	***-0.272***	-0.219	-0.052	-0.154	0.103	1.028	-0.016	**0.118**	0.805
		t-stat	0.806	0.791	-0.934	-1.034	-0.627	-1.032	-0.888	-1.560	-1.249	-0.298	-0.874	0.583		-0.441	0.897	
New Zealand	NZ Composite	coef. (%)	0.040	-0.082	-0.024	**0.058**	-0.102	-0.001	0.033	-0.073	-0.172*	0.049	-0.017	-0.014	1.307	0.008	**0.032**	0.261
		t-stat	0.665	-0.954	-0.286	0.675	-1.227	-0.009	0.399	-0.873	-2.042	0.586	-0.201	-0.163		0.443	0.511	
Poland	General	coef. (%)	0.271*	-0.141	-0.316	**0.019**	-0.363*	-0.216	-0.315	-0.259	-0.505**	-0.365*	-0.266	-0.100	1.584	0.010	0.260*	4.157*
		t-stat	2.220	-0.804	-1.840	0.107	-2.068	-1.235	-1.835	-1.489	-2.912	-2.137	-1.510	-0.567		0.278	2.039	
South Africa	All Share Index	coef. (%)	0.148	-0.106	-0.171	-0.015	-0.164	-0.171	-0.198	***-0.219***	-0.217	-0.027	-0.115	**0.020**	0.979	0.021	**0.127**	1.905
		t-stat	1.679	-0.835	-1.363	-0.116	-1.314	-1.350	-1.621	-1.754	-1.717	-0.217	-0.919	0.160		0.777	1.380	
Slovenia	Ljubljana	coef. (%)	0.182	***-0.270***	-0.170	-0.054	-0.253	-0.196	-0.139	0.338*	-0.047	0.034	0.019	-0.165	3.077**	0.095**	**0.087**	0.729
		t-stat	1.867	-1.940	-1.313	-0.404	-1.919	-1.486	-1.051	2.482	-0.343	0.250	0.134	-1.153		3.314	0.854	
United States	NYSE Composite	coef. (%)	0.759**	-0.746*	-0.719*	-0.698*	-0.668*	-0.772*	-0.754*	-0.826*	-0.811*	-0.675*	-0.669*	-0.647*	0.894	0.034	0.725**	9.188**
		t-stat	3.314	-2.251	-2.244	-2.148	-2.068	-2.394	-2.298	-2.540	-2.434	-2.080	-2.015	-1.968		0.483	3.031	

Panel (a) and panel (b) present the regression results, that is, the regression coefficients, t and F statistics for the following equations, respectively:

$R_t = \beta_1 + \beta_2 Feb_t + \beta_3 Mar_t + \beta_4 Apr_t + \beta_5 May_t + ... + \beta_{12} Dec_t + \varepsilon_t$

$R_t = \alpha_0 + \alpha_i Jan_t + e_t$

All coefficients have been presented as percentages (multiplied by 100) since most of them became almost zero after rounding to decimal 3. This could have been avoided from the outset by calculating rates of return as percentages rather than as fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold and "***Bold Italic***" denote the regression coefficients for the months of the year that give the highest and lowest mean daily returns, respectively. Note that in Panel (b) only the coefficients giving the highest mean daily returns have been marked in bold.

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

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Overall, Panel (b) of Table 11.6 suggests that all the markets have some January effect, but it is only significant for Poland (at the 5% level) and the US (at the 1% level). For the African markets, a significant January effect was found for most of the markets. Only the BRVM indices and Botswana's DCI did not have a January effect.

11.3.5 Week-of-the-month effect

For the week-of-the-month effect, the hypothesis was to find which week of the month gives the highest mean daily returns. For all the benchmarking markets, the first week of the month gives the highest mean daily returns, and these are significant for Australia, Brazil, Poland, South Africa, Slovenia and the US. For Poland and South Africa, daily index returns are significantly explained by the weeks of the month, and to a lesser extent for Australia.

Table 11.7: Regression results for week-of-the-month effect

Country	Index		(C=WK1)	WK2	WK3	WK4	F-stat
Australia	Ordinary	coef. (%)	0.075*	-0.142**	0.000	-0.064	4.413**
		t-stat	2.320	-3.120	0.010	-1.460	
Brazil	BOVESPA	coef. (%)	0.234*	-0.262	-0.153	-0.238	1.275
		t-stat	2.210	-1.751	-1.026	-1.639	
Finland	HEX Index	coef. (%)	**0.144**	-0.235	-0.111	-0.048	1.328
		t-stat	1.620	-1.872	-0.881	-0.399	
Malaysia	KLSE Index	coef. (%)	**0.047**	-0.055	-0.018	-0.136	0.746
		t-stat	0.659	-0.543	-0.176	-1.366	
New Zealand	NZ Composite	coef. (%)	**0.054**	-0.113*	-0.003	-0.055	2.308
		t-stat	1.543	-2.279	-0.068	-1.169	
Poland	General	coef. (%)	**0.255****	-0.339**	-0.243*	-0.296**	4.395**
		t-stat	3.505	-3.297	-2.358	-2.975	
South Africa	All Share Index	coef. (%)	**0.203****	-0.216**	-0.187*	-0.266**	5.137**
		t-stat	3.883	-2.927	-2.533	-3.732	
Slovenia	Ljubljana	coef. (%)	**0.136***	-0.094	-0.005	-0.040	0.609
		t-stat	2.452	-1.199	-0.064	-0.518	
United States	NYSE Composite	coef. (%)	**0.344***	-0.348	-0.312	-0.316	1.428
		t-stat	2.495	-1.788	-1.602	-1.699	

The table present the regression results, that is, the regression coefficients, t and F statistics for the equation:

$$R_t = \beta_1 + \sum_{i=2}^{4} \beta_i WKi_t + \varepsilon_t$$

All coefficients have been presented as percentages (multiplied by 100) since most of them became almost zero after rounding to decimal 3. This could have been avoided from the outset by calculating rates of return as percentages rather than as fractions.

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

Bold denotes the regression coefficient for the week of the month that gives the highest mean daily return.

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

For the African markets, the highest mean returns are not specific to one particular week and are mostly not significant. The highest mean daily returns are in the first week of the month and are significant only for Zimbabwe's Industrial Index. The weeks of the month significantly explain the stock returns for the BRVM and for Egypt.

11.3.6 The Kruskal-Wallis ANOVA and median tests

Table 11.8: Kruskal-Wallis ANOVA and median[#] tests for seasonal effects

	WEEKDAY[a]		MONDAY[b]		TOM DAYS[c]		TOM[d]		TOM DAYS2[e]		TOM2[f]	
Country	Kruskal-Wallis H-stat	Chi-Square	Kruskal-Wallis H-stat	Chi-Square	Kruskal-Wallis H-stat	Chi-Square	Kruskal-Wallis H-stat	Chi-Square	Kruskal-Wallis H-stat	Chi-Square	Kruskal-Wallis H-stat	Chi-Square
Australia	1.384	0.942	0.197	0.254	9.450	10.096	5.602*	3.496	10.765	11.311*	4.347*	2.686
Brazil	7.710	9.153	5.559*	4.203*	11.625*	7.878	5.993*	4.704*	8.052	5.262	3.598	2.135
Finland	11.262*	9.445	0.615	1.325	11.003	12.806*	6.562*	7.379**	7.309	9.160	3.344	4.113*
Malaysia	19.786**	19.467**	16.995**	10.320**	4.552	6.522	1.394	2.548	2.508	4.099	1.539	2.397
New Zealand	14.305**	13.987**	10.139**	9.570**	10.889	6.387	3.396	1.481	8.0268	5.294	1.449	0.596
Poland	10.394*	8.386	1.834	0.647	13.745*	9.381	9.076**	6.408*	6.500	4.343	3.726	2.700
South Africa	7.383	9.115	5.463*	7.634**	17.375**	16.960**	13.921**	14.738**	18.753**	20.579**	13.252**	16.059**
Slovenia	26.217**	21.278**	3.589	2.097	16.475**	16.416**	3.448	5.994*	10.856	12.612*	2.339	5.383*
United States	6.082	6.213	5.141*	2.860	18.126**	12.262*	5.965*	1.570	21.814**	12.113*	8.686**	2.472

(Continued)

	TOY DAYS[g]		TOY[h]		MONTH[i]		JANUARY[j]		WEEK[k]	
Country	Kruskal-Wallis H-stat	Chi-Square	Kruskal-Wallis H-stat	Chi-Square	Kruskal-Wallis H-stat	Chi-Square	Kruskal-Wallis H-stat	Chi-Square	Kruskal-Wallis H-stat	Chi-Square
Australia	6.656	5.215	1.111	0.735	12.698	10.116	0.005	0.134	13.398**	10.810*
Brazil	9.533	8.919	3.428	5.239*	6.912	12.954	0.007	0.050	8.414*	6.926
Finland	8.564	7.305	5.777*	5.225*	7.566	2.989	0.142	0.005	3.029	4.627
Malaysia	9.987	10.802	0.005	0.082	18.259	14.719	0.886	0.355	3.029	5.303
New Zealand	11.747*	10.841	4.248*	2.041	16.403	14.472	0.292	0.086	6.025	3.889
Poland	18.729**	14.564*	12.077**	8.164**	20.591*	16.781	4.614*	3.457	11.282*	5.300
South Africa	4.338	5.000	0.371	0.023	14.477	13.772	1.885	0.006	15.218**	11.434**
Slovenia	12.873*	9.007	1.350	0.367	37.213**	29.564**	2.205	0.383	2.551	2.712
United States	8.530	8.572	1.593	0.681	12.015	11.153	0.058	0.167	1.640	0.618

[#] The Median test statistic in the table is labelled "Chi-square"

** and * imply statistical significance for a two-tailed test at the 1% and 5% levels, respectively

[a] Codes 1-5 used to represent days from Monday to Friday

[b] Codes 0 and 1 used to represent 'all other days of the week' and 'Mondays', respectively

[c] Code 0 is used to represent all the other days of the month, and codes 1-5 are used to represent each of the turn-of-month days, beginning with the last trading day of the previous month and ending on the fourth trading day of the current month

[d] Codes 0 and 1 are used to represent days 'for the rest of the month' and 'for the turn-of-month', respectively

[e] Code 0 is used to represent all the other days of the month, and codes 1-5 are used to represent each of the turn-of-month days, beginning with the last trading day of the previous month and ending on the fourth trading day of the current month, after extracting the turn-of-year effect

[f] Codes 0 and 1 are used to represent days 'for the rest of the month' and 'for the turn-of-month', respectively, after extracting the turn-of-year effect

[g] Code 0 is used to represent all the other days of the year, and codes 1-5 are used to represent each of the turn-of-year days, beginning with the last trading day of the year and ending on the fourth trading day in January

[h] Codes 0 and 1 are used to represent days 'for the rest of the year' and 'for the turn-of-year', respectively

[i] Codes 1-12 are used to represent each of the 12 months of the year with 1 for January and 12 for December

[j] Code 1 used to represent the January days and 0 to represent the days for the remaining months of the year

[k] Codes 1-4 used to represent each of the weeks of the month, with 1 for the first week and 4 for the last week of the month

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

Table 11.8 shows a significant day-of-the-week (DOW) effect for Finland, Malaysia, Poland, New Zealand and Slovenia using the Kruskal-Wallis test. Using the Chi-square Median test no DOW effect is observed for Finland and Poland. The Monday effect is observed using both the Kruskal-Wallis and Chi-square tests for Brazil, Malaysia, New Zealand and South Africa, and for the US using only the Kruskal-Wallis test. There is a turn-of-the-month effect for South Africa, Slovenia and the U.S. using both the Kruskal-Wallis and Chi-square tests, and for Brazil and Poland using only the Kruskal-Wallis test. When only two codes are used, '1' to represent all the turn-of-month days and '0' otherwise, Australia also exhibits a TOM effect, while the effect becomes less significant for the U.S.

After extracting the turn-of-the-year effect, the TOM effect completely disappears for Brazil, Finland and Poland. For the other markets, it still exists though to a lesser extent. The U.S. and Malaysia did not exhibit any of the TOY, the month-of-year, January and the week-of-month effects using the Kruskal-Wallis and Chi-square tests. For the TOY effect, whereby each TOY day is represented by a different code, is significant for Poland, using both tests, and for New Zealand and Slovenia using the Kruskal-Wallis tests. The TOY effect continues to be significant for Poland and New Zealand but cease to exist for Slovenia when only two codes are used; '1' for the TOY days and '0' otherwise. It, however, becomes significant using the Chi-square test for Brazil and Finland. Only the two Eastern European markets, Poland and Slovenia, exhibit a month-of-the-year effect, with both the Kruskal-Wallis and median tests, and with only the Kruskal-Wallis test, respectively.

A January effect is also found only for Poland using the Kruskal-Wallis test and does not exist for any other market including the U.S. The week-of-the-month effect is found to exist only for Australia, Brazil, Poland and South Africa. The Kruskal-Wallis and median test results are different from those found for the African markets in the previous chapter. While the TOM effect observed for Egypt disappeared after extracting the TOY effect, it continues to exist for some of the benchmarks in this study. Also the month-of-the-year effect was more prevalent than the other effects for the African markets but it only exist in one benchmarking market in this chapter. Only the Egyptian indices exhibited a week-of-the-month effect as compared to four benchmarking markets with significant week-of-the-month effects.

Tables 11.9 and 11.10 summarise the results and highlight the markets with similar patterns between the African stock markets in the previous chapter and the benchmarks. However, evidence of anomalies is still not accepted to indicate inefficiency of markets. Proponents of the EMH/CAPM theory suggest that although there are some deviations from the norm, the EMH/CAPM combination is irreplaceable, and its validity needs no empirical proof. While the 'anomalies literature', referred to as behavioural finance, tries to abandon and replace the EMH/CAPM paradigm, Fama (1998) argues that until behavioural finance proves itself to be better than the EMH/CAPM, it does not matter how many 'anomalies' are discovered, the EMH/CAPM will still stand (Frankfurter and McGoun, 2001).

Table 11.9: Day/period giving highest or lowest returns from regression analysis

Description	Day	Benchmarks		African stock markets	
		Significant	Not significant	Significant	Not significant
Day-of-Week Effect					
Day giving the lowest mean daily returns	**Mon**	Malaysia, New Zealand	Brazil	Botswana2	Botswana3, Zimbabwe1, Zimbabwe2
	Tues		Slovenia	-	Mauritius2, Morocco, Namibia2, Tunisia1, Tunisia2
	Wed	Poland	Finland, South Africa	-	Egypt1, Egypt2
	Thurs	-	-	-	Botswana1, BRVM1, BRVM2, Mauritius1, Namibia1
	Fri	-	Australia, U.S.	-	-
Day giving the highest mean daily returns	**Mon**	Poland	South Africa	-	BRVM2
	Tues	-	-	-	BRVM1
	Wed	-	Australia	-	Botswana1, Namibia1, Namibia2, Tunisia1, Zimbabwe1
	Thurs	-	U.S.	Morocco	Tunisia2
	Fri	Brazil, Malaysia, New Zealand, Slovenia	Finland,	Botswana2, Botswana3	Egypt1, Egypt2, Mauritius1, Mauritius2, Zimbabwe2
Monday/ Weekend Effect					
Day giving the lowest mean daily returns	**Mon**	Brazil, Malaysia, New Zealand	Australia, Slovenia, U.S.	Botswana2, Botswana3, Morocco	Botswana1, BRVM1, Egypt1, Egypt2, Mauritius1, Mauritius2, Namibia1, Tunisia1, Zimbabwe1, Zimbabwe2
	ROW	-	Finland, Poland, South Africa	-	BRVM2, Namibia2, Tunisia2
End/ Turn-of-the-Month Effect					
Days giving the highest mean daily returns	**EOMN1**	Finland	-	-	BRVM1, BRVM2, Ghana
	EOMP1	South Africa, U.S.	-	-	Botswana1, Tunisia1, Tunisia2
	EOMP2	Australia, Brazil, New Zealand	-	Botswana2, Botswana3	Zimbabwe1
	EOMP3	Slovenia	-		Morocco, Namibia2, Zimbabwe2
	EOMP4	Malaysia, Poland	-	MAURITIUS2	Egypt1, Egypt2, Mauritius1, Namibia1

Description	Day	Benchmarks		African stock markets	
		Significant	Not significant	Significant	Not significant
	ODM	-	-	-	-
		Turn-of-Month Effect			
Period giving the highest mean daily returns	**TOM**	Australia, Finland, New Zealand, Poland, South Africa, U.S.	Brazil, Malaysia, Slovenia	Botswana2, Botswana3, Egypt1, Egypt2, Mauritius1, Mauritius2	Botswana1, Namibia1, Namibia2, Tunisia2, Zimbabwe1, Zimbabwe2
	ROM	-	-	Ghana	BRVM1, BRVM2, Morocco, Tunisia1
		Turn-of-Month Effect*			
Period giving the highest mean daily returns	**TOM***	Australia, Finland, South Africa	Brazil, Malaysia, New Zealand, Poland, Slovenia, U.S.	Botswana2, Botswana3,	Botswana1, Egypt1, Egypt2, Mauritius1, Mauritius2, Namibia1, Namibia2
	ROM*	-	-	Ghana, Zimbabwe1	BRVM1, BRVM2, Morocco, Tunisia1, Tunisia2, Zimbabwe2
		End/ Turn-of-the-Year Effect			
Days giving the highest mean daily returns	**JANN1**	-	Malaysia	BRVM1, BRVM2, Zimbabwe2	Botswana1, Ghana, Namibia1
	JANP1	Finland, Poland, U.S.	-	Egypt1, Egypt2	-
	JANP2		Brazil, New Zealand	-	Zimbabwe1
	JANP3	Australia, South Africa	-	Namibia2	Morocco
	JANP4	-	Slovenia	-	Botswana2, Botswana3, Mauritius1, Mauritius2, Tunisia1, Tunisia2
	ODY	-	-	-	-
		Turn-of-Year Effect			
Period giving the highest mean daily returns	**TOY**	Poland, U.S.	Australia, Brazil, Finland, New Zealand, South Africa, Slovenia	Egypt1, Egypt2, Zimbabwe1	Botswana2, Botswana3, BRVM1, BRVM2, Ghana, Mauritius1, Mauritius2, Namibia2, Tunisia2, Zimbabwe2
	ROY	-	Malaysia	Botswana1	Morocco, Namibia1, Tunisia1
		Month-of-Year/ January Effect			
Month giving the highest mean daily returns	**Jan**	U.S.	-	Egypt1, Egypt2, Mauritius1, Mauritius2, Tunisia1, Tunisia2, Zimbabwe1	-
	Feb	-	Malaysia	-	Botswana2, Botswana3
	Mar	-	-	-	-
	Apr		Australia, New Zealand, Poland	Ghana	-
	May	-	-	-	Namibia2
	Jun	-	-	-	-
	Jul	-	-	-	-
	Aug	Slovenia	-	Botswana1, Morocco	Zimbabwe2
	Sep	-	-	-	-
	Oct	-	Finland	-	-
	Nov	-	Brazil	-	Namibia1
	Dec	-	South Africa	BRVM1, BRVM2	-
Month giving the lowest mean daily returns	**Jan**	-	-	BRVM1, BRVM2	-
	Feb	-	Slovenia	-	-
	Mar	-	-	-	-
	Apr	-	-	Tunisia1, Tunisia2	-
	May	-	-	Mauritius1	-

Description	Day	Benchmarks		African stock markets	
		Significant	Not significant	Significant	Not significant
	Jun	-	-	Egypt1	-
	Jul	-	-	Egypt2, Morocco	-
	Aug	U.S.	Brazil, Finland, Malaysia, South Africa	Namibia1	Botswana2
	Sep	New Zealand, Poland	Australia	Mauritius2	Botswana1, Botswana3, Ghana
	Oct	-	-	-	-
	Nov	-	-	Zimbabwe1	Namibia2
	Dec	-	-	-	Zimbabwe2
			January Effect		
Month giving the highest mean daily returns	Jan	Poland, U.S.	Australia, Brazil, Finland, Malaysia, New Zealand, South Africa, Slovenia	Egypt1, Egypt2, Mauritius1, Mauritius2, Tunisia1, Tunisia2, Zimbabwe1	Botswana2, Botswana3, Ghana, Morocco, Namibia1, Namibia2, Zimbabwe2
	OMY	-	-	Botswana1	BRVM1, BRVM2
			Week-of-the-month Effect		
Week giving the highest mean daily returns	Wk 1	Australia, Brazil, Poland, South Africa, Slovenia, U.S.	Finland, Malaysia, New Zealand	Zimbabwe1	Botswana2, Botswana3, Egypt1, Egypt2,
	Wk 2	-	-	-	Ghana, Morocco, Namibia1
	Wk 3	-	-	-	Botswana1, Mauritius1, Mauritius2, Namibia2, Tunisia1
	Wk 4	-	-	-	BRVM1, BRVM2, Tunisia2, Mining

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

Table 11.10: Significant effects (at the 5% level) using the Kruskal-Wallis and median tests

Effect	Benchmarks		African stock markets	
	Kruskal-Wallis	Chi-square	Kruskal-Wallis	Chi-square
DOW	Finland, Malaysia, New Zealand, Poland, Slovenia	Malaysia, New Zealand, Slovenia	Botswana2, Botswana3, Morocco, Zimbabwe1	Botswana2, Botswana3, Egypt1, Egypt2, Morocco, Zimbabwe1
TOM	Australia, Brazil, Finland, Poland, South Africa, U.S.	Brazil, Finland, Poland, South Africa, Slovenia	Eypt1, Egypt2	Egypt2
TOM2	Australia, South Africa, U.S.	Finland, South Africa, Slovenia	-	-
TOY	Finland, New Zealand, Poland	Brazil, Finland, Poland	Egypt1, Egypt2, Mauritius2, Zimbabwe1	Egypt1, Egypt2, Mauritius1, Zimbabwe1
MONTH	Poland, Slovenia	Slovenia	Botswana1, BRVM1, BRVM2, Ghana, Morocco, Tunisia1, Zimbabwe1	Botswana1, BRVM1, BRVM2, Ghana, Morocco, Zimbabwe1, Zimbabwe2
JAN	Poland	-		
WEEK	Australia, Brazil, Poland, South Africa	Australia, South Africa	Egypt1, Egypt2	-

Key to 11.9 and 11.10: Botswana1=Domestic Companies Index, Botswana2=Foreign Companies Index, Botswana3= All Companies Index, BRVM1=BRVM-10 Index, BRVM2=BRVM-Composite Index, Egypt1=Hermes Financial Index, Egypt2=EFGI, Ghana=Ghana stock Exchange Index, Mauritius1=SEMDEX, Mauritius2=SEMTRI, Morocco=CFG25, Namibia1=Overall Index, Namibia2=Local Index, Tunisia1=BVMT, Tunisia2=TUNINDEX, Zimbabwe1=Industrial Index, Zimbabwe2=Mining Index

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

11.4 Conclusion

This chapter investigated seasonal effects on the JSE and the markets from other regions used as benchmarks to the markets studied in the previous chapter. The results suggest that there are some differences between these markets and the African markets in the previous chapter. These differences cannot be attributed to statistical artefacts such as the distribution of returns. The distribution of returns is almost similar for all the markets with the returns relatively deviating from the normal distribution. Seasonal effects cannot, however, be said to be attributed to geographical location of the market. In other words, the time lag hypothesis is not supported in this study. It, however, seems that the seasonal effects are subject to the period being investigated. While some studies have found patterns to exist on some markets for certain countries, the same patterns are not observed in this study.

While the benchmarks show a tendency to have their highest returns in the first week of the month, no clear pattern was observed for the African markets in the pervious chapter. The month-of-the-year effect was, however, the strongest for the African markets but is only observed for two indices for the benchmarking countries. It would therefore be interesting to investigate what explains the existence of seasonal effects on African stock markets, as the explanations given for other markets may be inapplicable. This is suggested for future research.

12 CONCLUSIONS AND RECOMMENDATIONS

As stock markets continue to emerge on the African continent, the perception that these markets are not efficient has prevailed. This is because little research has been done on these markets to support or refute their informational efficiency. The first African study on market efficiency to find its way into an international academic journal was a study by Dickinson and Muragu (1994) on the Kenyan stock market. Later studies have recently appeared in overseas journals and these include Smith, *et al.* (2002) and Appiah-Kusi and Menyah (2003) that examine the serial correlation in index returns.

Considering that these markets are thinly traded, researchers have done very little to correct for the thin trading bias, except for a few studies such as Appiah-Kusi and Menyah (2003), who used the adjustment method by Miller, *et al.* (1994) for index returns. The existence of such thin trading has mostly been taken as given on small stock markets with no effort being made to examine the extent of the problem.

Despite the increasing doubt regarding the relevance of linear models in testing the EMH, especially for small markets such as those in Africa, no effort has been made to examine if the data series are indeed nonlinear. However, models such as the GARCH have simply been adopted in tests for the EMH based on nonlinearity and time-varying risk assumptions. Although current research has shifted focus to finding evidence that contradicts the EMH such as seasonal anomalies, the size and P/E effects, there has been very little similar research done on the African stock markets with one exception namely the JSE.

The objective of this thesis was to reduce the disparity in the EMH research between African stock markets and stock markets elsewhere. The thesis investigated whether there are any patterns that can be exploited for abnormal gains on African stock markets by testing the RWH. The thesis also covered relevant issues relating to the EMH, such as EMH anomalies, in line with similar capital markets research ongoing in other markets. Particular attention has been given to the thin trading effect. The robustness of nonlinearities and out-of-sample predictabilities of African stock indices thin trading indicated that there are some differences in the results, especially when the observed serial correlation coefficients and Z-values are used as the tested variables. It is suggested that this could partly explain the contradictory random walk evidence for African stock markets found in the literature. However, the differences using binary data were mostly insignificant. The autocorrelation in the observed individual stock returns that is attributable to thin trading was also found to be minimal.

The out-of-sample predictabilities of African stock market indices using both linear and nonlinear models, and benchmarking with the random walk model, were also investigated. This is another interesting approach to testing the RWH. The random walk hypothesis would be negated if the random walk model fails to outperform the alternative models. The findings, as presented in Chapter 8, show that eleven out of the seventeen indices studied are best forecast out-of-sample by a model that is nonlinear in the conditional mean while the linear first-order autoregressive model gives superior performance in forecasting directional change. The random walk model only gave the best performance in two highly correlated indices, Botswana's FCI and ACI.

An investigation of the size and P/E effects on the African stock markets conducted in Chapter 9 indicated that the two effects are mostly either in reversed form to those assumed in the literature or non-existent. While literature suggests that small firms have higher average long-run returns, which are equilibrium compensation for bearing the high risk associated with such stocks, there is no compelling evidence in this study to indicate that small firms have higher realised returns. Instead of the usual small-firm premium, a large-firm premium is mostly observed, suggesting a reversed size effect. This is, however, consistent with studies such as Dimson and Marsh (1999) and Horowitz, *et al.* (1999) who also concluded from their findings that perhaps the size premiums have been reversed. According to Horowitz, *et al.* (2000), it appears that the size effect is a typical academic discovery; strong in-sample evidence, weak out-of sample results.

When examining the P/E effect, it was found that it is largely the high P/E portfolios that give the highest returns. These results from the portfolio analysis are also confirmed by the regression analysis, where positive slope coefficients are observed for both size and the P/E ratios. Contrary to what has been observed in other markets, the size effect on African stock markets does not seem to be related to seasonal effects. The January effect does not seem to influence small firm asset returns differently to large firm assets.

In Chapter 10, significant seasonal effects are found on some, but not all of the African indices. The strongest effect observed is the month-of-the-year followed by the day-of-the-week effect. While most indices exhibited the highest mean daily returns in January, the BRVM indices exhibited a reversed "December decline - January rise" pattern. Using the Kruskal-Wallis and median tests, the turn-of-the-month effect observed for Egypt disappeared after the turn-of-the-year effect was removed. While no seasonal effects were observed for Namibia using the Kruskal-Wallis and median tests, at least one seasonal effect was observed for the other markets, suggesting some exploitable opportunities for abnormal gains.

The investigation of seasonal patterns was extended to markets in other regions. The results in Chapter 11 indicate that there are some differences in seasonal patterns between African markets and markets in other regions. These differences are, however, not clearly defined, except for the week-of-the-month and the month-of-the-year effects. While the benchmarks showed a tendency to have their highest returns in the first week of the month, no clear pattern was observed for the African markets. The month-of-the-year effect was, however, the strongest for the African markets, but was only observed for two indices of the benchmarking countries.

12.2 Implications and suggestions for future research

While the evidence provided in this thesis indicates some deviations from the random walk hypothesis, it does not necessarily imply weak-form inefficiency of the markets. It only suggests serial correlation in stock returns. Whether or not such serial correlation can be exploited for abnormal returns, net of transaction costs, is what determines whether or not these markets are weak form efficient. Therefore this thesis only provided the first step to determining the efficiency of African stock markets. Future research should focus on investigating if the deviation from the random walk observed in this thesis can be used in technical analysis to consistently obtain abnormal gains. Can trading strategies be formulated to trade actively and obtain returns above or in excess of the passive buy-and-hold strategy? This would shed more light on the acceptance or rejection of the EMH by the African markets studied.

Since transaction costs are presumed high on the African markets, it is possible that strategies formulated to exploit the patterns observed in this thesis may not produce economically significant profits after accounting for transaction costs. Even if investors who trade at very low costs can be in a position to implement such investment strategies, there might be some risks associated with holding such portfolios due to the thinness of African markets and thus the infrequent trading of stocks.

This thesis also investigated the statistical and econometric implications of thin trading in random walk tests. While some methods for correcting the thin trading bias in beta or systematic risk estimation are well established, methods for correcting the thin trading bias in market efficiency testing are not so clear-cut. It is hoped that the adjustment method adopted in this thesis will be critically evaluated and possibly modified for application in the efficiency testing of thinly traded markets. Since trading activity plays an important role in the predictability of short-horizon stock returns, further research should also focus on how thin trading impacts on investment decisions. Again, can trading strategies be devised that enable investors to profit from the thin trading on African stock markets uncovered in this thesis? If such rules exist, do they outperform the buy-and-hold strategy? Such explorations can give more insight on how thin trading affect the efficiency of markets.

One limitation to studies on thin trading is the difficulty in obtaining volume-traded data for some markets. One could use those markets where volume-traded data is available to build a model that can predict whether a zero return is a zero volume day. For example using the probit model, one can try to determine the probability that an observed zero return is a zero volume day. One obvious regressor would be whether the return in the previous day was a zero return where none of the right-hand side variables should contain volume information.[1] Such an investigation, in addition to finding the source of infrequent trading on African stock markets, also provides a fascinating avenue for future research.

Despite the significant deviation from normality observed herein, some of the methods used are parametric. These methods are dependent on the normality and finite variance assumptions. For example, the degree of correlation between successive returns captured by the serial correlation is one of the methods used to test for weak-form efficiency. Such tests, however, require normality of the return distribution. The findings in this study were, however, substantiated with some nonparametric methods. However, the runs test, which has been used as the nonparametric test for the random walk, though essentially a first generation statistical test, is also not adequate in shedding light on the weak form efficiency of the markets studied. Future research should use other methods, which are less dependent on the distribution of returns such as technical trading rules.

It should also be noted that the EFAR model discussed in this thesis is not being suggested as the plausible nonlinear model for forecasting African stock indices. While the transition functions for the STAR models are well established, the exponential feedback function used for the EFAR model is novel. It is expected that other nonlinear models could have more forecasting power than the EFAR. Other complex models, such as the artificial neural networks (ANN), besides being less dependent on the distribution of returns, have been found to consistently outperform alternative models in providing higher risk-adjusted returns on other markets. Future research on African stock markets should also consider use of the ANN models in out-of-sample forecasting. It would also be interesting to investigate if profitable trading strategies can be devised from these nonlinear models to select investment portfolios that provide superior risk-adjusted returns after adjusting for transaction costs. Further work is needed to help understand the causes and structure of this nonlinear predictability in African stock markets and the forces driving price movements.

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[1] This suggestion was made by an anonymous referee.

In this thesis dynamic forecasting is used, whereby the sample size is continuously enlarged with the forecast values. However in real life, there is no reason why investors would not use new information as it becomes available. Therefore, it will be interesting to also investigate if nonlinear models would still give the best performance - outperform the random walk - in static (one-step-ahead) predictions, whereby the sample size is continuously enlarged by the observed values.

Although this was beyond the control of the researcher, the periods of investigation used in this thesis are rather short. This is because most African stock markets do not have long histories of data. There is, however, a need for follow-up studies on the same issues covered in this thesis as longer histories of data become available. For example, the availability of systematic published data at the firm level could facilitate more comprehensive studies on cross-sectional predictabilities in the future. Because African stock markets have large quantities of thinly traded stocks, future research should also use methods that correct for the thin trading bias in efficiency testing.

The investigations in this thesis used data that possibly suffer from survivorship bias, especially in the examination of size and P/E effects. While the possible existence of the bias was acknowledged, its effect on the findings was not examined although it deserves attention. It is also possible that a greater proportion of delisted stocks and acquisitions are small-stock losers. Future research investigating the size and P/E effects should try and use data that is free of survivorship bias.

While most studies investigating cross-sectional predictabilities use deciles to group stocks into portfolios, the small size nature of markets studied in this thesis resulted in a reduction in the number of portfolios used to sort stocks to only three. If size and P/E effects were a violation of market efficiency, the small size and illiquidity of African markets, therefore, would reduce or eliminate the potential benefits of strategies aimed at exploiting this inefficiency.

Although the findings in this thesis add to the existing list of conclusions regarding the small-cap versus the large-cap stocks, they present more challenging questions that deserve further research. The thesis, however, did not attempt to find answers to these questions. While Hameed and Ting (2000) suggested that one possible explanation why large-firm size portfolios earn higher returns than small firm-size portfolios is that heavily and frequently traded securities tend to earn substantially higher contrarian profits than low trading activity portfolios, the question is whether the same suggestion can be used to explain the reversed size effect on African stock markets? What explains the fact that high P/E stocks give the highest returns? Can investment strategies be formulated to trade profitably in large-firm and growth stocks on African stock markets? Answers to these and other questions arising from this study call for further investigation.

Although some seasonal patterns were observed, it is also important to investigate the dynamics of these patterns on African stock markets. While the weekend effect is said to have disappeared or been reversed for the U.S. market, further research on African stock markets can also reveal if the seasonal patterns observed in this study are persistent or only specific to the periods investigated. Further research is also required to investigate if the seasonal patterns exist on African stock markets for the same reason they exist on stock markets elsewhere. Such an investigation may reveal new factors that are specific to African stock markets. Another interesting area of research would be to investigate if the seasonal patterns observed herein can be exploited for abnormal gains. For example, seasonal effects such as the day-of-the-week effect may only have practical value to those investors who were already planning to trade and pay transaction costs.

Traditional tests of the RWH have generally focused on the returns either of individual securities or portfolios of securities. Although the cross-sectional interaction of security returns over time is an important aspect of stock price dynamics, studies on African stock markets have given little attention to cross-autocorrelations. Findings (e.g. Lo and MacKinlay, 1990) suggest that stock returns are often positively cross-autocorrelated, and the majority of profits in contrarian portfolio strategies are due to the cross effects among securities. It is suggested that cross effects display a lead-lag relation in size-related portfolios, with the returns of larger stocks generally leading those of smaller ones.

12.3 Challenges and limitations

Evidence contrary to the EMH is not easily acceptable, especially by the proponents or supporters of the EMH theory. According to Frankfurter and McGoun (2001), even though "anomalies" to the EMH/CAPM have been known to exist since the very beginning of their testing, actions have been taken to adjust the EMH/CAPM to address such disconfirming evidence. The authors suggested that most studies on the issue seem like deliberate attempts at immunization of the theory with less attention being given to fundamentals:

> "Traditional finance has immunised itself from criticism by ensuring that its novices in doctoral programs receive a limited education in its own bastardised version of the philosophy of science and by clothing itself in terms that are so attractive and its opposition in terms that are so disparaging. Real progress in finance can only be achieved when such matters are recognised for what they are and critically examined." (Frankfurter and McGoun, 2001: 427)

In determining if trading strategies, technical and/or fundamental, devised can be used to trade profitably for abnormal gains requires a benchmark. In most cases asset-pricing models such as the market model and the CAPM are used. This gives rise to the joint hypothesis problem in that these models could be misspecified. Evidence such as size and the P/E effects, for example, have been considered inconsistent with the predictions of these familiar models and could be potential alternative sources of risk. However, proponents of the CAPM argue that variables, such as size and P/E may simply be proxies for measurement error in betas. They also argued that since the market portfolio can never be measured, the CAPM model cannot be tested and therefore no evidence constitute violation of the CAPM.

12.4 Recommendations

Although operational inefficiency does not constitute informational inefficiency, African stock markets have a lot to gain by improving their operational efficiencies. Current views are that the characteristics of emerging and developed markets are differentiated. The differences are in the operational, legal, institutional, and technological infrastructure. However, as emerging markets mature in the quality of their institutional infrastructure and their characteristics converge towards those of developed economies, the differences between the two will become less apparent. One consideration for improving the operational efficiencies of African stock markets is by integrating them into regional stock exchanges. However, the stumbling block to this development is the fact that national stock exchanges are considered symbols of national pride in most African countries. This has unfortunately resulted in less cooperation in integrating the stock exchanges, yet the improved liquidity and efficiency that comes with it is of great importance in attracting foreign portfolio investment to the continent.

African countries also need to embrace information technology such as the Internet and make it accessible and affordable to all members of society. Whereas key infrastructures to Internet accessibility, such as a home telephone and computer, are still considered luxury items in some African countries, the Internet has played a major role in advancing stock market development in developed countries. While foreign residents from developed countries have greater Internet accessibility than African residents, they are restricted in their participation on African stock markets by regulations and lack of online up-to-date local information content. It is therefore very important for African stock markets to open up to foreign participation and to avail local content on the Internet to promote foreign participation. This would, hopefully, improve their liquidity and efficiency. The elimination of regulatory or institutional features that inhibit short-term trading might also create potential for arbitrage. This suffices to eliminate profit opportunities and thus promote the pricing efficiency of African stock markets.

African stock markets should ensure the timely release of public information. The real-time Stock Exchange News Service (SENS) launched by the JSE in 1997 in an attempt to enhance market transparency and investor confidence could be replicated by other African stock markets. Just as on the JSE, it should be made a requirement for all listed stocks to disseminate any corporate news or price sensitive information on a system like the SENS prior to using any other media or outlet. The JSE's automated 'JET' trading system is said to give warning when company-specific, price-sensitive information is about to be released on SENS, so that investors can reconsider their share dealings. A well-coordinated information dissemination system would substantially improve investor participation and thus the efficiency of African markets.

As African financial markets continuously reform to promote capital deepening, continuous research on stock markets such as their efficiency, equity valuation, performance and risk are necessary to determine the effectiveness of such reforms. Research will also keep investors informed on the developments of the African stock markets. Governments can also play a major role in promoting research by putting incentives into place for both academic institutions and investment companies. Through continuous research, investment managers will be able to identify mispriced assets and in trying to profit from such mispricing will arbitrage away the abnormal gains and drive the markets to efficiency.

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APPENDICES

Appendix A: List of companies included in this study according to stock exchange

Company	Full/Known Company Name
	Botswana (1035 trading days)
BAC	Barclays Bank Botswana
BIH	Botswana Insurance Holdings
ENG	Engen Botswana
FNB	First National Bank Of Botswana
INC	Inco Holdings
MTF	Metro Sefalana Cash And Carry
PEP	Pep Botswana Holdings
PFN	Profurn JSE
RDC	RDC Properties
SEC	Sechaba Brewery Holdings
SEF	Sefalana Holdings Company
STC	Standard Chartered Bank Of Botswana
	BRVM (687 trading days)
BICC	BICI
BNBC	BERNABE
CABC	SICABLE
CIEC	CIE
FTSC	FILTISSAC
NTLC	NESTLE
PHC	PH
PRSC	PEYRISAC
SAFC	SAFCA
SAGC	SAGA
SDCC	SODE
SDVC	SDV
SEMC	SIEM
SGBC	SGB
SHEC	SHELL
SLBC	SOLIBRA
SMBC	SMB
SNTS	SONATEL Senegal
SOGC	SOGBCI
SRIC	SARI
STAC	SETAO
STBC	SITAB
TTRC	TRITURAF
UNXC	UNIWAX
	Egypt (1342 trading days)
ALXP	Alexandria Pharmaceuticals
ALXW	Alexandria Spinning & Weaving
AISC	Alexandria National Iron & Steel
APCC	Alexandria Portland Cement
ABCE	Arab Ceramic
CAPL	Cairo Poultry
CIB	Commercial International Bank
DLNS	Delta Insurance
EAB	Egyptian American Bank
EDLT	East Delta Flour Mills
EDBK	Export Development Bank Of Egypt
EFND	Egyptian Financial & Industrial
EGCM	Egyptian Chemical Industrial
EGSR	Egyptian Starch & Glucose
ECAB	Egyptian Electric Cables
ELKA	El Kahera Housing & Development
ELND	El Nasr Dehydrated
ELSG	El Nasr Clothes & Textiles

Company	Full/Known Company Name
EWBK	El Watany Bank Of Egypt
ETBC	Eastern Tobacco
EXOL	Extracted Oils Derivatre
HHSE	Heliopolis Housing Construction
HCST	Hoechst Orient
HPCC	Helwan Portland Cement
INEG	Industrial Engineering Construction & Development
KZAY	Kafr El Zayat Pesticides
MPHS	Memphis Pharmaceuticals
MIBK	Misr International Bank Sae
MDGM	Middle Egypt Flour Mills
MWST	Middle & West Delta Flour Mills
MSCM	Misr Chemical Industries
MHOT	Misr Hotels (Hilton)
MOIL	Misr Gulf Oil Processing
MHBK	Mohands Bank
MHIN	Mohandes Insurance
NTCM	National Cement
NBDV	National Bank For Development
NCAI	North Cairo Grinding Mills
NLMT	Nile Match Company
NLPM	Nile Pharmaceuticals
NCTY	Nasr City Housing
NSGB	National Societe General Bank
ORNT	Orient Linen & Cotton Weavers
PCHC	Paint & Chemical Industrials (Pachin)
PFIZ	Pfizer Egypt
RKTA	Rakta
SCAI	South Cairo Grinding
SGEN	Societe General Pour Les
SZCN	Suez Canal Bank
SZCM	Suez Cement
TORA	Torah Portland Cement
UHDV	United Housing & Development
UPAC	Unipack
URAB	Unirab Weaving
UPGL	Upper Egypt Flour Mills
	Ghana (754 trading days)
ABL	Accra Brewery
AGC	Ashanti Goldfields
ALW	Aluwork
BAT	British American Tobacco
CFAO	CFAO Ghana
EIC	Enterprise Insurance
FML	Fan Milk
GBL	Ghana Breweries
GCB	Ghana Commercial Bank
GGL	Guinness Ghana
HFC	Home Finance
MGL	Metalloplastica Ghana
MLC	Mechanical Lloyd
MOGL	Mobil Oil Ghana
PAF	Pioneer Aluminium Factory
PZ	PZ Ghana
SCB	Standard Chartered Bank
SPPC	Super Paper Products
SSB	SSB Bank

Company	Full/Known Company Name
UNIL	Unilever Ghana
Kenya (1366 trading days)	
ABM	A Baumann & Company
BAM	Bamburi Portland Cement
BAT	British American Tobacco Kenya
BBD	Brooke Bond Kenya
BBK	Barclays Bank Of Kenya
BOC	BOC Kenya
CBG	Crown Berger Kenya
CFC	CFC Bank
CGN	Car & General Kenya
CMC	CMC Holdings
CRB	Carbacid Investiments
CTS	City Trust
DLP	Dunlop Kenya
DTK	Diamond Trust (Kenya)
EBL	East African Breweries
ECB	East African Cables
ECD	ICDC Investment
EGD	Eaagads
EPK	East African Packaging
EPT	East African Portland Cement
EXP	Express Kenya
FST	Firestone East Africa
GWK	Williamson Tea Kenya
HFC	Housing Finance
JUB	Jubilee In.
KCB	Kenya Commercial Bank
KNL	Kenya Oil
KNM	Kenya National Mills
KPL	Kenya Power & Lighting
NBK	National Bank Of Kenya
NIC	National Industrial Credit
NMG	National Media Group
PFR	Pan African Insurance
RVP	Rea Vipingo Plantations
SBK	Standard Chartered Bank Of Kenya
SNG	Standard Newspapers
SSN	Sasini Tea & Coffee
TTL	TTL Kenya
UCH	Uchumi Supermarkets
UNG	Unga Group
Mauritius (1197 trading days)	
AIRM	Air Mauritius
HAPP	Happy World Foods
IREL	Ireland Blythe
MCB	MCB
NMH	New Mauritius Hotel
ROG	Rogers
STBK	State Bank Of Mauritius
SUNR	Sun Resorts
UTDB	United Basalt Products
Morocco (1349 trading days)	
ACR	ACRED
ATH	AUTO - HALL
BAL	BALIMA
BCE	BMCE

Company	Full/Known Company Name
BCI	BMCI
BCM	BCM
BDE	BNDE
BER	BERLIET - M
BNM	BRANOMA
CDM	CDM CREDIT DU MAROC
CIH	CIH CDT.IMMOB.HOTELIER
CLT	CENTRALE LAITIERE
CMA	CIMENTSM
CRD	CREDOR
CRN	CARNAUD
CSR	COSUMAR
CTM	CTM - LN
DIS	DIAC - SALAF
EQD	EQDOM
FRT	FRT
GTM	GENERAL - TIRE
HOL	HOLCIM MAROC
LCT	LECARTON
LES	LESIEUR
LGM	LGMC
LGT	LONGOMETAL
NEX	NEXANS
ONA	ONA
OUL	OULMES
REB	REBABCIE
SBM	BRASSERIE DU MAROC
SID	SONASID
SNI	SNI
SOF	SOFAC
WFB	WAFABANK
ZDJ	ZELLIDJA
Namibia (1341 trading days)	
AOX	Afrox [JSE]
API	African Portland Industries
BLW	Barloworld [JSE]
CIC	CIC Holdings
GNB	Genbel [JSE]
KOL	Kolosus Holdings [JSE]
MRL	Metropolitan Life [JSE]
MTF	Mutual & Federal Insurance [JSE]
NAS	Namibian Sea Products [JSE]
NBS	Namibia Breweries
NCT	Nictus [JSE]
NMC	Namibian Minerals Corporation [Toronto, Nasdaq]
NMF	Namibian Fishing Industry [JSE]
PNB	PEP Namibia Holdings
SRM	Sentra Namibia
STB	Standard Bank Corporation
Tunisia (1250 trading days)	
ALIQ	AIR LIQUIDE
ALK	ALKIMIA
AB	AMEN BANK
ALSE	AMEN LEASE
AMS	AMS
ASTR	ASTREE
ATB	ATB

Company	Full/Known Company Name
ATL	ATL
BH	BH
BIAT	BIAT
BNA	BNA
BS	BS
BT	BT
BTA	BTEI ADP
CIL	CIL
ECF	ICF
LCT	La CARTE
MPX	MONOPRIX
PB	PALM BEACH
PBA	PALM BEACH ADP
PTUN	PLACEMENT TUN
SFBT	SFBT
SIMP	SIMPAR
SITX	SITEX
SOFI	SOFI SICAF
SPDT	SPDIT
STAR	STAR
STB	STB
STIL	STIL
TVST	TUNINVEST SICAR
TAIR	TUNISAIR
TLAI	TUNISIE LAIT
TLSE	TUNISIE LEASING
UBCI	UBCI
UIB	UIB
Zimbabwe (1353 trading days)	
APEX	Apex Corporation of Zimbabwe
ARIS	Ariston Holdings
ASHA	Ashanti Goldfields (Zimbabwe)
BARC	Barclays Bank of Zimbabwe
BICC	Bicc Cafca
BIND	Bindura Nickel
BORD	Border Timbers
CAPS	Caps Holdings
CHEM	Chemco Holdings
CIRC	Circle Cement
CLAN	Clan Holdings
COLC	Colcom Holdings
DELT	Delta Corporation
DWHI	David Whitehead Textiles
EDGA	Edgars Stores (Zimbabwe)
FALC	Falcon Investments (Zimbabwe)
FALG	Falcon Gold Zimbabwe
FINH	Zimbabwe Financial Holdings
GULL	Gulliver Consolidated
HIPP	Hippo Valley Estates
HSLY	Haddon & Sly
HUNY	Hunyani Holdings
KING	Kingdom Financial Holdings
MEIK	Meikles Africa
NATF	National Foods Holdings
NTS	National Tyre Services
PGI	PG Industries Zimbabwe
RADA	Radar Holdings

Company	Full/Known Company Name
RIO	Rio Tinto Zimbabwe
SEED	Seed Company of Zimbabwe
TA	TA Holdings
TANG	Tanganda Tea
TEDC	Tedco
TRUW	Truworths
TSL	Tobacco Sales
WCOL	Wankie Colliery
ZPAP	Zimbabwe Newspapers
ZPLO	Zimplow
ZSUN	Zimbabwe Sun

APPENDIX B

THE AFRICAN STOCK MARKETS

----------*A BRIEF REVIEW OF EACH MARKET*----------

Appendix B: A brief review of each market

The **Algerian** Stock Exchange was inaugurated as part of the banking reform programme. The stock exchange is still in its early stages of development with only three companies listed. It is managed by the Société de gestion de la bourse des valeurs and is supervised by a Securities and Exchange Commission, Commission d'organisation et de surveillance des operations de bourse (COSOB).

The **Botswana** Share Market was established to act as a vehicle to sell the Botswana Development Corporation's investments. It officially became the Botswana Stock Exchange in 1995 and is governed by the Botswana Stock Exchange Act. The Exchange is responsible for the operation and regulation of the equities and fixed interest securities market. It plays a pivotal role in Botswana's financial system as an avenue through which government and the private sector can raise debt and equity capital.

The Abidjan Stock Exchange in the **Ivory Coast** was the only stock exchange in the francophone West African countries before it was closed on 31 December 1997, leading to the formation of the BRVM in 1998. The BRVM is a regional stock exchange, which serves 8 French-speaking member countries of the West African Economic and Monetary Union (UMOEA), namely, Benin, Burkina Faso, Côte d'Ivoire, Guinea Bissau, Mali, Niger, Senegal and Togo.

The **Egyptian** Stock Exchange, or CASE, dates back more than 100 years. The Exchange was very active in the 1940s ranking fifth in the world, but suspended operations in 1961. The CASE was revived in 1992 under the Egyptian government's restructuring and economic reform programme, which led to the enactment of the Capital Market Law No.95. The Exchange established a company devoted to information dissemination, the Egyptian Information Dissemination (EGID).

The **Ghana** Stock Exchange (GSE) was incorporated as a private company limited by guarantee under the Ghana Companies Code of 1963 (Act 179). In October 1990 the Exchange was given recognition as an authorised stock exchange under the Stock Exchange Act of 1971 (Act 384). It changed its status in April 1994 to a public company limited by guarantee. Under the Securities Industry Law (SIL) PNDCL333 of 1993, the apex regulatory body for the securities market is the Securities and Exchange Commission (SEC). The other regulatory body is the GSE Council. The SIL also provides for the establishment of a Fidelity Fund from which persons who suffer financial loss from any defalcation committed by a Stock Exchange member-company is compensated.

In **Kenya**, dealing in shares and stocks started in the 1920s when the country was still a British colony. The Nairobi Stock Exchange, as it stands today, was constituted as a voluntary association of stockbrokers registered under the Societies Act in 1954. The business of dealing in shares was then confined to the resident European community since Africans and Asians were not permitted to trade in securities until after the attainment of independence in 1963. The Nairobi Stock Exchange operated as an association of stockbrokers with no trading floor until October 1991. The Capital Markets Authority (CMA) represents the Governments' interests on the exchange. The CMA, besides playing an active role in investor education, has an important regulatory function in securing the long-term prospects of the exchange.

The **Malawi** Stock Exchange (MSE) operates under the Capital Market Development Act 1990 and the Companies Act 1984. Prior to the listing of the first company, the major activities that were being undertaken on the exchange were the provision of a facility for secondary market trading in Government bonds namely, Treasury Bills and Local Registered Stocks. The regulatory legislation of the Stock Exchange, the Securities Act, is still to be passed into law by Parliament.

The **Mauritius** Stock Exchange was established as a private limited company under the Stock Exchange Act 1988. The Act also established the Stock Exchange Commission (SEC), which controls and supervises stock exchange operations. A major development was the successful implementation of a Central Depository System (CDS), in January 1997. The exchange operates two markets, the Official List and the Over-The-Counter Market (for unlisted shares).

Morocco's Casablanca Stock Exchange has seen three reforms since it was inaugurated in 1929. Under the 1948 reform, the Securities exchange acquired a legal personality. The 1967 reform involved a legal and technical reorganisation, and change in legal status to that of a public establishment. The third reform was initiated in 1993, amended and supplemented in 1996. This reform defined the various market players, and introduced a range of rules and technical procedures needed for the development of the Moroccan financial market.

Mozambique's Maputo Stock Exchange started operations with trading in treasury bonds worth more than $4.6m. The government is planning to sell off the shares it still holds in some of the 900 former state-run enterprises that have been privatised. This is expected to significantly boost the number of companies listed on the exchange.

The **Namibian** Stock Exchange was formed as an association of 37 Namibian businessmen and individuals who each contributed N$10 000 to raise start-up capital for the first three years of the existence of the exchange. The Government gave full moral and legislative support, including amending the 1985 Stock Exchanges Control Act. The initial listings were dual-listed companies with extensive operations in Namibia. The first Namibian-only listings and capital raising exercises started in 1994. The Stock Exchange operates under licence from the Ministry of Finance.

The **Nigerian** Stock Exchange was established in 1960 as the Lagos Stock Exchange. In December 1977 it became the Nigerian Stock Exchange, with branches established in some of the major commercial cities of the country, each with a trading floor. The branch in Lagos, the Head Office, was opened in 1961; Kaduna in 1978; Port Harcourt in 1980; Kano in 1989; Onitsha in February 1990 and Ibadan in August 1990. Recently another branch opened in Abuja. Legislation guiding transactions on the Nigerian stock market include the Investments & Securities Decree No. 45 of 1999, the Companies and Allied Matters Decree of 1990, the Nigerian Investment Promotion Commission Decree of 1995 and the Foreign Exchange (Miscellaneous Provisions) Decree of 1995. The regulatory bodies are the Nigerian Stock Exchange, as a self-regulatory organisation (SRO), and the Securities & Exchange Commission (SEC), which administers the Investments & Securities Decree of 1999. The deregulation of the capital market in 1993 saw the abrogation of the Exchange Control Act of 1962 and the Nigerian Enterprise Promotion Decree of 1989.

South Africa's JSE abolished the requirement that all stockbrokers must be South African citizens in 1995. The formal bond market passed from the JSE to the Bond Exchange of South Africa in 1996 and is licensed as a financial market in terms of the Financial Markets Control Act. The Listings division of the JSE introduced a real time news service, Stock Exchange News Service (SENS), in August 1997. SENS ensures early, equal and wide dissemination of all information that is expected to have an effect on the prices of securities that trade on the JSE.

In **Sudan**, the idea to establish a stock exchange was first brought up in 1962. The Act for a Securities Market was passed 20 years later, in 1982. In 1990 the process to put the necessary framework in place was initiated. In November 1992, the Securities Market Act of 1982 was approved. An Act to establish the exchange was passed in June 1994 with the primary market starting operations in October 1994 and the secondary market in 1995.

The **Swaziland** Stock Market (SSM) was established following consultation between the Minister for Finance and the Governor of the Central Bank of Swaziland on the benefits of having such an exchange. For eight years it operated as an over-the-counter, single-broker facility. It became a fully-fledged stock exchange following the advent of another broker in 1998. As a result, the Swaziland Stock Exchange (SSX) was inaugurated in July 2000 under the auspices of the Central Bank. Trading is conducted under the supervision of the Capital Markets Development Unit of the Central Bank, which has regulatory oversight over the operations of the exchange.

Tanzania's Dar es Salaam Stock Exchange (DSE) was incorporated in September 1996 as a private company limited by guarantee. It is a non-profit making body created to facilitate the Government implementation of the economic reforms and to encourage the wider share ownership of companies in Tanzania. The formation of the DSE followed the enactment of the Capital Markets and Securities Act 1994, and the establishment of the Capital Markets and Securities Authority (CMSA). The CMSA is the regulatory body charged with the mandate of promoting conditions for the development of capital markets in Tanzania and regulating the industry. Trading activity on the DSE commenced in April 1998 after two years of background preparatory work under the stewardship of the Government through the CMSA.

The **Tunis** Stock Exchange (TSE) was established in 1969. The 1998 market reforms aimed at increasing transparency and efficiency strengthened the market. Although small compared to other Arab markets, the TSE is relatively active.

The **Uganda** Securities Exchange (USE) commenced trading in January 1998 with just one instrument listed, a bond issued by the East African Development Bank. It is run under the jurisdiction of the Capital Markets Authority, which reports to the Central Bank of Uganda. The first listing on the exchange took place in January 2000. The first cross listing was a Kenyan company, East African Breweries Limited (EABL), in April 2001.

The Lusaka Stock Exchange (LuSE) in **Zambia** was established with preparatory technical assistance from the International Finance Corporation (IFC) and the World Bank in 1993 and opened its doors in February 1994. The rules and listing requirements on the LuSE are backed up by supporting legislation enacted as the Securities Act No 38 of 1993. The Securities Act regulates the entire Zambian securities market. It creates and defines a central market in which both unlisted and listed securities trade on the exchange as opposed to the dual market system. The Securities Act established the Securities and Exchange Commission (SEC) as a corporate body and it is given powers under the Act to regulate and supervise the securities industry in Zambia.

Zimbabwe's first stock exchange opened in 1896 in Bulawayo and operated for six years. The present Zimbabwe Stock Exchange was founded in 1946 in Bulawayo and in December 1951, a second floor was opened in Harare. In January 1974, the Zimbabwe Stock Exchange Act was promulgated as Act 27 of 1973 (Chapter 198) which formalised the establishment of the present Zimbabwe Stock Exchange (ZSE) in Harare. The ZSE is regulated by the Zimbabwe Stock Exchange Act (Chapter 24.18 of 1996). It operates under the supervision of a nine-member committee composed of seven representatives of stockbrokerage companies and two government-nominees. The ZSE is required by its Act to maintain a security fund, part of which comes from members' contributions.

APPENDIX C

CORRELATION RESULTS USING WORLD BANK DATA

--------*INTERNET STATISTICS & STOCK MARKET DEVELOPMENT INDICATORS*--------

Appendix C: The Relationship between Internet infrastructure and accessibility, other information dissemination media and stock market development

C1: Non-African countries

Spearman's rho Correlations - Countries outside Africa

	EPI	INDEX	MCAP	MCAP%	STO-CKS	VAL%	T/O%	CELL	PC	INTEL	TEL US	TELOC	TELI NES	TEL CITY	TEL RAT	TEL REV	TEL IST	TEL-TIME	WWW	RA-DIO	TV
EPI	1.000																				
INDEX	.224**	1.000																			
MCAP	.768**	.256**	1.000																		
MCAP%	.504**	.332**	.811**	1.000																	
STOCK	.537**	-.031	.707**	.454**	1.000																
VAL%	.677**	.176*	.861**	.786**	.651**	1.000															
T/O%	.517**	.105	.619**	.385**	.621**	.802**	1.000														
CELL	.235**	.088	.546**	.656**	.183**	.598**	.340**	1.000													
PC	.118	.143*	.494**	.621**	.088	.553**	.278**	.872**	1.000												
INTEL	-.338**	.111	.066	.445**	-.306**	.190**	-.072	.416**	.523**	1.000											
TELUS	-.134	-.027	-.455**	-.507**	-.253**	-.505**	-.303**	-.719**	-.657**	-.315**	1.000										
TELOC	.102	.120	.265**	.154**	.021	.199**	.166**	.393**	.434**	.062	-.379**	1.000									
TELINE	.399**	.148*	.574**	.476**	.290**	.480**	.325**	.645**	.555**	.034	-.515**	.349**	1.000								
TELCIT	.169*	.022	.282**	.318**	.124	.347**	.363**	.693**	.748**	.109	-.524**	.279**	.621**	1.000							
TELRA	.116*	.152*	.457**	.581**	.128**	.530**	.307**	.819**	.926**	.419**	-.619**	.408**	.601**	.861**	1.000						
TELREV	.171**	.199**	.501**	.622**	.055	.469**	.140**	.634**	.622**	.655**	-.465**	.321**	.347**	.196**	.484**	1.000					
TELIST	.258**	-.157	-.432**	-.563**	-.046	-.498**	-.247**	-.735**	-.847**	-.618**	.554**	-.386**	-.485**	-.438**	-.763**	-.725**	1.000				
TELTIM	-.303**	-.219**	-.631**	-.658**	-.223**	-.625**	-.364**	-.782**	-.836**	-.476**	.600**	-.418**	-.579**	-.508**	-.763**	-.714**	.893**	1.000			
WWW	*.628***	*.023*	*.815***	*.548***	*.680***	*.720***	*.607***	*.623***	*.495***	*-.098**	*-.607***	*.302***	*.619***	*.515***	*.494***	*.289***	*-.372***	*-.556***	*1.000*		
RADIO	.025	.059	.351**	.419**	.106	.423**	.275**	.645**	.704**	.209**	-.541**	.478**	.444**	.572**	.752**	.332**	-.634**	-.597**	.478**	1.00	
TV	.170**	.135	.423**	.442**	.128**	.457**	.299**	.707**	.789**	.270**	-.536**	.492**	.479**	.727**	.828**	.458**	-.660**	-.685**	.476**	.756**	1.000

**. Correlation is significant at the .01 level (2-tailed).

*. Correlation is significant at the .05 level (2-tailed).

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

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C2: African countries

Spearman's rho Correlations _ African countries

	EPI	MCAP	MCAP%	STOCKS	VAL%	T/O%	CELL	PC	INTEL	TELOC	TELINES	TELCITY	TELRAT	TELREV	TELIST	TELTIME	WWW	RADIO	TV
EPI	1.000																		
MCAP	.585**	1.000																	
MCAP%	.587**	.661**	1.000																
STOCKS	.275	.897**	.541**	1.000															
VAL%	.596**	.706**	.765**	.624**	1.000														
T/O%	.528**	.592**	.438**	.561**	.704**	1.000													
CELL	.384**	.141	.444**	.105	.337**	.255*	1.000												
PC	.176	.181	.491**	.108	.584**	.242	.605**	1.000											
INTEL	-.3*	-.655**	-.362**	-.676**	-.405**	-.338**	.011	.049	1.000										
TELOC	.344*	-.140	-.064	-.279*	-.234	.025	-.082	-.245	.101	1.000									
TELINES	.372**	.381**	.469**	.189	.527**	.309*	.583**	.671**	-.190	-.190	1.000								
TELCITY	.300	.187	.503**	.171	.533**	.111	.613**	.768**	.015	-.311*	.705**	1.000							
TELRAT	.458**	.293*	.593**	.174	.647**	.233	.594**	.856**	-.115	-.341**	.863**	.883**	1.000						
TELREV	.021	-.183	-.271*	-.162	-.407**	-.194	-.178	-.215	.312**	.618**	-.541**	-.543**	-.435**	1.000					
TELIST	.039	.624**	.315*	.759**	.443**	.337*	-.193	-.211	-.696**	-.440**	.059	-.142	.062	-.403**	1.000				
TELTIME	-.7**	-.203	-.488**	.063	-.310*	-.063	-.554**	-.583**	-.037	-.145	-.656**	-.622**	-.640**	.104	.335*	1.000			
WWW	*.249*	*.615***	*.346***	*.696***	*.489***	*.517***	*.504***	*.363***	*-.466***	*-.162*	*.375***	*.290**	*.304***	*-.128*	*.280**	*-.238*	*1.000*		
RADIO	.312	.348*	.405*	.279	.349*	.358*	.361*	-.026	-.302*	-.035	.133	.178	.046	-.263	.289	-.082	.275	1.000	
TV	.567**	.404**	.382**	.222	.381**	.408**	.387**	.438**	-.267*	.029	.746**	.473**	.578**	-.356**	.002	-.334*	.331**	.209	1.000

**. Correlation is significant at the .01 level (2-tailed).

*. Correlation is significant at the .05 level (2-tailed).

Key to Appendix tables C1 and C2

CODE	DESCRIPTION	CODE	DESCRIPTION	CODE	DESCRIPTION
EPI	Portfolio investment, equity (DRS, current US$)	CELL	Mobile phones (per 1,000 people)	TELRAT	Telephone mainlines (per 1,000 people)
INDEX	S&P/IFC investable index (annual % change)	PC	Personal computers (per 1,000 people)	TELREV	Telephone revenue per mainline (current US$)
MCAP	Market capitalization of listed companies (current US$)	INTEL	International telecom, outgoing traffic (minutes per subscriber)	TELIST	Telephone mainlines, waiting list (thousands)
MCAP%	Market capitalization of listed companies (% of GDP)	TELUS	Telephone average cost of call to US (US$ per three minutes)	TELTIME	Telephone mainlines, waiting time (years)
STOCKS	Listed domestic companies, total	TELOC	Telephone average cost of local call (US$ per three minutes)	WWW	Internet users
VAL%	Stocks traded, total value (% of GDP)	TELINES	Telephone mainlines per employee	RADIO	Radios (per 1,000 people)
T/O%	Stocks traded, turnover ratio (%)	TELCITY	Telephone mainlines in largest city (per 1,000 people)	TV	Television sets (per 1,000 people)

Data used in the Analysis was obtained from the World Development Indicators Fact book 2002

Source: Chipo Mlambo (2004), University of Stellenbosch Business School

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APPENDIX D

TABLES FOR DATA NORMALITY

----------*DESCRIPTIVE STATISTICS AND DATA NORMALITY*----------

Appendix D: Descriptive statistics and data normality

Stock	N	Normal Parameters		Minimum	Maximum	Most Extreme Differences			Kolmogorov-Smirnov			Lilliefors p	Shapiro-Wilk W-stat
		Mean	Std. Dev.			Absolute	Positive	Negative	Z-stat	d-stat	p		
Botswana													
BAC	608	0.00138	0.01218	-0.06899	0.12516	0.35263	0.35263	-0.34473	8.69515***	0.35263	<.01	<.01	0.51875***
BIH	440	0.00266	0.01301	-0.08855	0.08855	0.33938	0.33108	-0.33938	7.11888***	0.33938	<.01	<.01	0.5284***
ENG	103	0.00194	0.00563	-0.02037	0.02429	0.28353	0.28353	-0.27763	2.87754***	0.28353	<.01	<.01	0.64366***
FNB	510	0.00237	0.01496	-0.09531	0.11123	0.32937	0.32358	-0.32937	7.43813***	0.32937	<.01	<.01	0.56714***
INC	231	0.00198	0.01086	-0.05716	0.08004	0.29096	0.29096	-0.28479	4.42228***	0.29096	<.01	<.01	0.66486***
MTF	167	0.00133	0.01342	-0.13353	0.07119	0.332	0.26748	-0.332	4.29043***	0.332	<.01	<.01	0.38486***
PEP	152	0.00014	0.01585	-0.09531	0.0816	0.34556	0.34556	-0.21365	4.2604***	0.34556	<.01	<.01	0.64322***
PFN	65	-0.00346	0.04076	-0.17688	0.22314	0.25631	0.24759	-0.25631	2.06643***	0.25631	<.01	<.01	0.55112***
RDC	105	0.00385	0.02276	-0.06697	0.18232	0.32304	0.32304	-0.28219	3.31021***	0.32304	<.01	<.01	0.43639***
SEC	677	0.00072	0.01204	-0.06832	0.10536	0.37456	0.37456	-0.33888	9.74584***	0.37456	<.01	<.01	0.58244***
SEF	326	0.00131	0.01606	-0.13976	0.08816	0.27791	0.27791	-0.2589	5.01776***	0.27791	<.01	<.01	0.64099***
STC	516	0.001	0.01111	-0.06579	0.10789	0.35946	0.35946	-0.35371	8.16545***	0.35946	<.01	<.01	0.53896***
BRVM													
BICC	299	0.00288	0.01937	-0.06306	0.09667	0.41533	0.41533	-0.33454	7.1817***	0.41533	<.01	<.01	0.54544***
BNBC	224	-0.00108	0.01843	-0.07788	0.07228	0.33397	0.33397	-0.33088	4.99842***	0.33397	<.01	<.01	0.55641***
CABC	149	-0.0014	0.01175	-0.07796	0.03615	0.3417	0.33506	-0.3417	4.17099***	0.3417	<.01	<.01	0.46633***
CIEC	496	0.00151	0.02415	-0.07796	0.07233	0.28891	0.28891	-0.22323	6.43436***	0.28891	<.01	<.01	0.79323***
FTSC	256	0.00218	0.02455	-0.12927	0.13538	0.31211	0.31211	-0.27204	4.99383***	0.31211	<.01	<.01	0.69231***
NTLC	345	0.00027	0.01355	-0.07793	0.0721	0.35418	0.35418	-0.35262	6.57856***	0.35418	<.01	<.01	0.55728***
PHC	103	-0.00366	0.01789	-0.07781	0.05129	0.34473	0.34473	-0.3156	3.49862***	0.34473	<.01	<.01	0.57644***
PRSC	162	-0.00114	0.00776	-0.07796	0.01428	0.47269	0.41095	-0.47269	6.01635***	0.47269	<.01	<.01	0.21286***
SAFC	36	0.00048	0.01303	-0.02084	0.07232	0.48693	0.48693	-0.32749	2.92156***	0.48693	<.01	<.01	0.33521***
SAGC	89	0.00192	0.01789	-0.07796	0.07217	0.4195	0.4195	-0.30859	3.95759***	0.4195	<.01	<.01	0.50318***
SDCC	310	0.00029	0.02131	-0.07796	0.07234	0.35701	0.35701	-0.31969	6.28576***	0.35701	<.01	<.01	0.6702***
SDVC	254	0.00052	0.01487	-0.07796	0.09762	0.3872	0.3872	-0.33304	6.171***	0.3872	<.01	<.01	0.52206***
SEMC	106	0.0037	0.0281	-0.07794	0.07232	0.34486	0.34486	-0.2313	3.55058***	0.34486	<.01	<.01	0.72398***
SGBC	198	0.0052	0.02895	-0.07796	0.12095	0.34946	0.34946	-0.23359	4.91737***	0.34946	<.01	<.01	0.74907***
SHEC	425	-0.00153	0.01918	-0.13976	0.1764	0.35765	0.35765	-0.3485	7.3731***	0.35765	<.01	<.01	0.50185***
SLBC	117	-0.00264	0.0156	-0.07796	0.06447	0.35267	0.33024	-0.35267	3.81466***	0.35267	<.01	<.01	0.48829***
SMBC	264	0.00078	0.01616	-0.0961	0.11999	0.34088	0.31917	-0.34088	5.53866***	0.34088	<.01	<.01	0.52546***
SNTS	664	-0.00015	0.01696	-0.07796	0.16132	0.31705	0.30403	-0.31705	8.16968***	0.31705	<.01	<.01	0.65481***
SOGC	250	0.00265	0.02596	-0.07791	0.07232	0.31176	0.31176	-0.24039	4.92934***	0.31176	<.01	<.01	0.73086***
SRIC	95	-0.00159	0.0094	-0.07535	0.03279	0.41334	0.37852	-0.41334	4.02876***	0.41334	<.01	<.01	0.33249***
STAC	34	-0.00091	0.00343	-0.01446	0.00414	0.3976	0.33665	-0.3976	2.31841***	0.3976	<.01	<.01	0.47003***
STBC	361	0.0001	0.01673	-0.08376	0.08388	0.33839	0.33839	-0.29281	6.42932***	0.33839	<.01	<.01	0.63008***
TTRC	361	-0.00096	0.01515	-0.07796	0.07188	0.33154	0.31413	-0.33154	6.29926***	0.33154	<.01	<.01	0.62336***
UNXC	128	-0.00242	0.01239	-0.0778	0.0381	0.34715	0.34715	-0.30343	3.92758***	0.34715	<.01	<.01	0.45554***
Egypt													
ALXP	397	0.00186	0.02123	-0.05454	0.05124	0.12376	0.10122	-0.12376	2.46594***	0.12376	<.01	<.01	0.93519***
ALXW	805	-0.00305	0.03085	-0.19679	0.11518	0.08941	0.07695	-0.08941	2.53668***	0.08941	<.01	<.01	0.93161***
AISC	573	-0.00067	0.02073	-0.05129	0.0495	0.12777	0.0745	-0.12777	3.05843***	0.12777	<.01	<.01	0.94684***
APCC	1192	-0.00016	0.02784	-0.14416	0.37897	0.09052	0.09052	-0.06939	3.12514***	0.09052	<.01	<.01	0.85598***
ABCE	537	-0.00126	0.02457	-0.06252	0.09971	0.1055	0.1055	-0.09816	2.44472***	0.1055	<.01	<.01	0.95192***
CAPL	538	0.00038	0.02579	-0.14318	0.04884	0.12813	0.12813	-0.128	2.97195***	0.12813	<.01	<.01	0.92714***
CIB	1275	-0.00064	0.02316	-0.27354	0.22135	0.08201	0.08154	-0.08201	2.92847***	0.08201	<.01	<.01	0.88368***
DLNS	573	-0.00053	0.01975	-0.05129	0.04879	0.14086	0.13324	-0.14086	3.37187***	0.14086	<.01	<.01	0.92341***
EAB	1250	-0.00128	0.02473	-0.16661	0.09588	0.07252	0.07252	-0.06875	2.56385***	0.07252	<.01	<.01	0.96636***
EDLT	1273	-0.00088	0.02308	-0.19532	0.09531	0.10473	0.10473	-0.07273	3.73658***	0.10473	<.01	<.01	0.8799***
EDBK	1209	-0.00049	0.0206	-0.21932	0.04879	0.10819	0.10819	-0.10306	3.76191***	0.10819	<.01	<.01	0.85584***
EFND	1231	-0.00066	0.02366	-0.144	0.10536	0.08068	0.08068	-0.06618	2.83056***	0.08068	<.01	<.01	0.96807***
EGCM	631	-0.00011	0.02778	-0.22314	0.19045	0.09754	0.09754	-0.09104	2.45023***	0.09754	<.01	<.01	0.91038***
EGSR	925	-0.00042	0.02285	-0.059	0.07152	0.07845	0.07845	-0.0697	2.38583***	0.07845	<.01	<.01	0.97629***
ECAB	1271	-0.00237	0.02672	-0.44414	0.08338	0.09551	0.09551	-0.07622	3.40495***	0.09551	<.01	<.01	0.80617***
ELKA	1255	-0.00249	0.03582	-0.67189	0.08701	0.08255	0.07298	-0.08255	2.92455***	0.08255	<.01	<.01	0.72002***
ELND	655	-0.00099	0.02444	-0.08649	0.06454	0.06957	0.06786	-0.06957	1.78043***	0.06957	<.01	<.01	0.9752***
ELSG	387	-0.00038	0.01957	-0.05129	0.04884	0.13576	0.13576	-0.10382	2.67072***	0.13576	<.01	<.01	0.91696***
EWBK	1264	-0.00068	0.0214	-0.18615	0.04888	0.10034	0.08746	-0.10034	3.5672***	0.10034	<.01	<.01	0.89779***
ETBC	1240	-0.00024	0.01969	-0.15149	0.04884	0.08713	0.08713	-0.0744	3.06831***	0.08713	<.01	<.01	0.93143***
EXOL	722	-0.00071	0.02811	-0.31807	0.09628	0.09654	0.09654	-0.09614	2.5939***	0.09654	<.01	<.01	0.88231***
HHSE	809	-0.0014	0.02364	-0.06691	0.08347	0.09536	0.09536	-0.08087	2.71235***	0.09536	<.01	<.01	0.96225***
HCST	494	-0.00043	0.02994	-0.05129	0.07796	0.09088	0.08582	-0.09088	2.01994***	0.09088	<.01	<.01	0.94025***
HPCC	1168	-0.00035	0.02211	-0.13981	0.11366	0.10707	0.10707	-0.08197	3.65909***	0.10707	<.01	<.01	0.94781***
INEG	770	-0.00137	0.02539	-0.07232	0.06899	0.06812	0.06812	-0.05909	1.89034***	0.06812	<.01	<.01	0.97153***
KZAY	989	-0.00014	0.02723	-0.09037	0.1984	0.06253	0.06253	-0.04687	1.96653***	0.06253	<.01	<.01	0.96497***
MPHS	636	0.00125	0.0232	-0.12226	0.10219	0.11179	0.09341	-0.11179	2.81924***	0.11179	<.01	<.01	0.94933***
MIBK	1256	-0.00138	0.02248	-0.25492	0.04881	0.08662	0.08662	-0.07675	3.06979***	0.08662	<.01	<.01	0.91687***
MDGM	1252	-0.00149	0.0249	-0.2071	0.07075	0.08229	0.08229	-0.05818	2.9116***	0.08229	<.01	<.01	0.93518***

Stock	N	Normal Parameters		Minimum	Maximum	Most Extreme Differences			Kolmogorov-Smirnov			Lilliefors p	Shapiro-Wilk W-stat
		Mean	Std. Dev.			Absolute	Positive	Negative	Z-stat	d-stat	p		
MWST	1262	-0.00101	0.02364	-0.24737	0.05704	0.08752	0.08752	-0.08482	3.10915***	0.08752	<.01	<.01	0.85924***
MSCM	1260	-0.00123	0.02889	-0.15673	0.07631	0.05908	0.04251	-0.05908	2.09704***	0.05908	<.01	<.01	0.96811***
MHOT	1092	0.00036	0.02607	-0.05129	0.09548	0.05335	0.05335	-0.04194	1.76292***	0.05335	<.01	<.01	0.9762***
MOIL	537	0.00008	0.01688	-0.05129	0.05108	0.15305	0.13096	-0.15305	3.54665***	0.15305	<.01	<.01	0.92093***
MHBK	839	-0.00086	0.03009	-0.09418	0.04879	0.0628	0.0628	-0.0433	1.81908***	0.0628	<.01	<.01	0.96043***
MHIN	634	0.00069	0.02576	-0.09478	0.09483	0.11232	0.11232	-0.08393	2.82803***	0.11232	<.01	<.01	0.95224***
NTCM	1064	-0.0002	0.03065	-0.15721	0.16799	0.06449	0.06306	-0.06449	2.10371***	0.06449	<.01	<.01	0.95931***
NBDV	1158	-0.00055	0.0263	-0.07171	0.09286	0.04097	0.03294	-0.04097	1.39423***	0.04097	<.05	<.01	0.97982***
NCAI	1213	-0.00143	0.02192	-0.24384	0.0597	0.0984	0.0984	-0.0879	3.42692***	0.0984	<.01	<.01	0.86858***
NLMT	1180	-0.00159	0.0258	-0.24412	0.04876	0.0675	0.06582	-0.0675	2.31878***	0.0675	<.01	<.01	0.89654***
NLPM	663	0.00155	0.01984	-0.1441	0.09976	0.10174	0.10078	-0.10174	2.61977***	0.10174	<.01	<.01	0.92432***
NCTY	1254	-0.00211	0.03136	-0.68452	0.04949	0.10361	0.10361	-0.10279	3.66913***	0.10361	<.01	<.01	0.68639***
NSGB	1188	-0.00031	0.02324	-0.2573	0.08794	0.09668	0.08111	-0.09668	3.33239***	0.09668	<.01	<.01	0.91899***
ORNT	345	-0.00144	0.03004	-0.05146	0.08004	0.09534	0.09534	-0.08985	1.7709***	0.09534	<.01	<.01	0.93955***
PCHC	1244	-0.00103	0.02211	-0.20059	0.06238	0.07928	0.07928	-0.06689	2.79625***	0.07928	<.01	<.01	0.94429***
PFIZ	1137	0.00136	0.03079	-0.11053	0.11572	0.05822	0.05822	-0.05691	1.96314***	0.05822	<.01	<.01	0.9647***
RKTA	749	0.00028	0.02985	-0.05735	0.05671	0.09336	0.09336	-0.07259	2.55495***	0.09336	<.01	<.01	0.94767***
SCAI	1229	-0.00131	0.02529	-0.21896	0.09885	0.07384	0.07384	-0.0603	2.5885***	0.07384	<.01	<.01	0.94142***
SGEN	382	0.00004	0.02364	-0.05129	0.05106	0.15948	0.15948	-0.12942	3.11696***	0.15948	<.01	<.01	0.92331***
SZCN	937	-0.00062	0.02988	-0.22981	0.27832	0.10801	0.09487	-0.10801	3.30612***	0.10801	<.01	<.01	0.82243***
SZCM	1277	-0.00035	0.02012	-0.11817	0.07104	0.07483	0.07483	-0.04766	2.6742***	0.07483	<.01	<.01	0.9725***
TORA	1267	-0.00087	0.02134	-0.14747	0.07899	0.10226	0.10226	-0.08735	3.63983***	0.10226	<.01	<.01	0.92668***
UHDV	1104	-0.00029	0.02835	-0.1331	0.05827	0.0495	0.0495	-0.04718	1.64478***	0.0495	<.01	<.01	0.96968***
UPAC	546	-0.003	0.02849	-0.05145	0.06415	0.07789	0.07789	-0.06503	1.82008***	0.07789	<.01	<.01	0.95789***
URAB	1211	-0.00186	0.03757	-0.68715	0.20131	0.09818	0.09818	-0.09732	3.41656***	0.09818	<.01	<.01	0.72914***
UPGL	1261	-0.00074	0.02252	-0.24223	0.06137	0.09283	0.09283	-0.06912	3.29642***	0.09283	<.01	<.01	0.90012***
Ghana													
ABL	236	0.00145	0.01832	-0.10536	0.11157	0.38795	0.29222	-0.38795	5.95973***	0.38795	<.01	<.01	0.50505***
AGC	172	0.00234	0.01975	-0.09309	0.16034	0.35216	0.34734	-0.35216	4.61852***	0.35216	<.01	<.01	0.47121***
ALW	544	0.00232	0.02871	-0.34657	0.22828	0.38589	0.38589	-0.36842	9.00032***	0.38589	<.01	<.01	0.40433***
BAT	448	0.00225	0.02362	-0.15415	0.18232	0.35945	0.34305	-0.35945	7.60817***	0.35945	<.01	<.01	0.49667***
CFAO	254	0.00154	0.02914	-0.11778	0.15082	0.35298	0.33599	-0.35298	5.62565***	0.35298	<.01	<.01	0.66042***
EIC	213	0.0041	0.02222	-0.05889	0.22314	0.36014	0.36014	-0.34244	5.25612***	0.36014	<.01	<.01	0.37567***
FML	406	0.00305	0.02712	-0.16974	0.16252	0.32348	0.32348	-0.32218	6.518***	0.32348	<.01	<.01	0.59123***
GBL	178	-0.00131	0.03893	-0.26236	0.26236	0.34833	0.34833	-0.34146	4.64736***	0.34833	<.01	<.01	0.44488***
GCB	684	0.00284	0.03227	-0.26236	0.38566	0.35232	0.33308	-0.35232	9.21447***	0.35232	<.01	<.01	0.46382***
GGL	483	0.00012	0.02672	-0.20624	0.18232	0.39051	0.30263	-0.39051	8.5824***	0.39051	<.01	<.01	0.46207***
HFC	258	0.0035	0.01539	-0.07155	0.1431	0.44663	0.44663	-0.3784	7.17397***	0.44663	<.01	<.01	0.34505***
MGL	143	0.00481	0.02157	-0.08514	0.10536	0.40721	0.40721	-0.35585	4.86953***	0.40721	<.01	<.01	0.49966***
MLC	258	0.00129	0.02622	-0.14842	0.11191	0.35242	0.32975	-0.35242	5.66071***	0.35242	<.01	<.01	0.55288***
MOGL	355	0.00296	0.02522	-0.09531	0.23889	0.32909	0.30933	-0.32909	6.20045***	0.32909	<.01	<.01	0.47118***
PAF	230	0.00494	0.03104	-0.10536	0.19683	0.411	0.411	-0.31395	6.23309***	0.411	<.01	<.01	0.47698***
PZ	181	0.00761	0.04503	-0.22014	0.34831	0.39614	0.39614	-0.36018	5.32947***	0.39614	<.01	<.01	0.41919***
SCB	412	0.00198	0.02074	-0.13353	0.12783	0.36723	0.35888	-0.36723	7.45395***	0.36723	<.01	<.01	0.50297***
SPPC	198	0.0029	0.02429	-0.1226	0.11157	0.32623	0.32071	-0.32623	4.59046***	0.32623	<.01	<.01	0.56344***
SSB	664	0.00125	0.02383	-0.12783	0.42887	0.37875	0.35007	-0.37875	9.75982***	0.37875	<.01	<.01	0.33804***
UNIL	517	0.00303	0.02455	-0.15415	0.21881	0.35069	0.3218	-0.35069	7.97379***	0.35069	<.01	<.01	0.44187***
Kenya													
ABM	127	-0.00219	0.01567	-0.10536	0.09157	0.275	0.27183	-0.275	3.09905***	0.275	<.01	<.01	0.54419***
BAM	763	-0.00057	0.0289	-0.18455	0.15415	0.17678	0.17678	-0.16748	4.8832***	0.17678	<.01	<.01	0.79325***
BAT	1012	0.0003	0.02755	-0.36464	0.27484	0.17591	0.17591	-0.16853	5.59595***	0.17591	<.01	<.01	0.58081***
BBK	1338	-0.00008	0.01938	-0.19513	0.23085	0.19817	0.12843	-0.19817	7.24887***	0.19817	<.01	<.01	0.76055***
BBD	617	-0.00025	0.01583	-0.17395	0.17275	0.22745	0.21825	-0.22745	5.64979***	0.22745	<.01	<.01	0.57805***
BOC	311	-0.00142	0.03787	-0.43825	0.43825	0.30497	0.30497	-0.29714	5.37824***	0.30497	<.01	<.01	0.2861***
CRB	371	-0.00062	0.01707	-0.08353	0.11157	0.18299	0.15933	-0.18299	3.52458***	0.18299	<.01	<.01	0.82391***
CGN	110	-0.00181	0.00887	-0.04879	0.01906	0.29856	0.18922	-0.29856	3.13134***	0.29856	<.01	<.01	0.74043***
CBG	595	-0.00013	0.03351	-0.30538	0.27721	0.1902	0.1902	-0.18284	4.63956***	0.1902	<.01	<.01	0.67675***
CFC	582	-0.00104	0.0256	-0.16252	0.19004	0.20595	0.20595	-0.1996	4.96849***	0.20595	<.01	<.01	0.71738***
CMC	456	-0.00118	0.02119	-0.15415	0.13461	0.19351	0.17662	-0.19351	4.13223***	0.19351	<.01	<.01	0.7464***
CTS	131	-0.00426	0.04855	-0.53492	0.05757	0.34022	0.29726	-0.34022	3.89395***	0.34022	<.01	<.01	0.22513***
DTK	733	-0.00139	0.02536	-0.30715	0.15006	0.19443	0.18347	-0.19443	5.26399***	0.19443	<.01	<.01	0.71976***
DLP	326	-0.00431	0.03591	-0.1643	0.42281	0.22091	0.22091	-0.20496	3.98859***	0.22091	<.01	<.01	0.57797***
EBL	1207	0.00043	0.01949	-0.15739	0.11394	0.17639	0.16578	-0.17639	6.12826***	0.17639	<.01	<.01	0.84511***
ECB	377	-0.00174	0.02501	-0.19062	0.17825	0.20222	0.19456	-0.20222	3.92649***	0.20222	<.01	<.01	0.69381***
EPK	143	-0.00081	0.01737	-0.0652	0.09844	0.20249	0.20249	-0.16546	2.42144***	0.20249	<.01	<.01	0.78253***
EPT	330	0.00193	0.02605	-0.18805	0.09531	0.17023	0.17023	-0.14802	3.09246***	0.17023	<.01	<.01	0.83065***
EGD	38	-0.00369	0.01816	-0.07232	0.03257	0.29635	0.19159	-0.29635	1.82685***	0.29635	<.01	<.01	0.67244***
EXPR	247	-0.00095	0.0222	-0.07696	0.20294	0.21968	0.21968	-0.16692	3.45248***	0.21968	<.01	<.01	0.70892***
FST	963	-0.00012	0.03004	-0.15541	0.49366	0.1752	0.1752	-0.14695	5.4369***	0.1752	<.01	<.01	0.69903***
GWK	398	0.0011	0.0198	-0.08961	0.21217	0.21115	0.21115	-0.17326	4.21248***	0.21115	<.01	<.01	0.66817***
HFC	1230	-0.00096	0.0344	-0.37156	0.42286	0.14694	0.12945	-0.14694	5.15328***	0.14694	<.01	<.01	0.77211***
ECD	1126	0.00024	0.02622	-0.25192	0.20717	0.16862	0.15287	-0.16862	5.65828***	0.16862	<.01	<.01	0.82416***

Stock	N	Normal Parameters		Minimum	Maximum	Most Extreme Differences			Kolmogorov-Smirnov			Lilliefors p	Shapiro-Wilk W-stat
		Mean	Std. Dev.			Absolute	Positive	Negative	Z-stat	d-stat	p		
JUB	717	-0.00078	0.01907	-0.10228	0.09699	0.16854	0.16854	-0.16201	4.51287***	0.16854	<.01	<.01	0.86436***
KCB	1327	-0.00123	0.03526	-0.43903	0.44869	0.16462	0.15609	-0.16462	5.99673***	0.16462	<.01	<.01	0.65534***
KNL	348	0.00173	0.02075	-0.11034	0.14778	0.21343	0.21343	-0.15898	3.98143***	0.21343	<.01	<.01	0.72708***
KNM	716	-0.00078	0.03949	-0.50253	0.32145	0.19408	0.18909	-0.19408	5.19335***	0.19408	<.01	<.01	0.65422***
KPL	1149	-0.00098	0.02694	-0.16459	0.32746	0.15244	0.14673	-0.15244	5.16738***	0.15244	<.01	<.01	0.77526***
NBK	1244	-0.00102	0.03851	-0.39803	0.23639	0.14702	0.14702	-0.14179	5.18559***	0.14702	<.01	<.01	0.82649***
NIC	1240	-0.00049	0.03024	-0.31508	0.3001	0.14838	0.14587	-0.14838	5.22512***	0.14838	<.01	<.01	0.73822***
NMG	1177	0.00023	0.04423	-1.07519	0.46563	0.25225	0.25225	-0.25131	8.65402***	0.25225	<.01	<.01	0.35547***
PFR	268	-0.00264	0.03993	-0.40547	0.14776	0.25928	0.25036	-0.25928	4.24455***	0.25928	<.01	<.01	0.51931***
RVP	908	-0.00137	0.03555	-0.24946	0.24014	0.16076	0.1388	-0.16076	4.84418***	0.16076	<.01	<.01	0.84433***
SSN	577	-0.00126	0.0257	-0.22314	0.11687	0.19746	0.19096	-0.19746	4.74322***	0.19746	<.01	<.01	0.65223***
SBK	1326	-0.00016	0.02822	-0.54712	0.44747	0.19396	0.18164	-0.19396	7.06309***	0.19396	<.01	<.01	0.53199***
SNG	467	0.00398	0.04541	-0.17535	0.43078	0.19341	0.19341	-0.13938	4.17966***	0.19341	<.01	<.01	0.78137***
TTL	877	-0.00167	0.02406	-0.17867	0.14518	0.16796	0.16796	-0.15245	4.97403***	0.16796	<.01	<.01	0.8167***
UCH	1222	-0.00016	0.03227	-0.40024	0.40547	0.17405	0.17068	-0.17405	6.08414***	0.17405	<.01	<.01	0.60268***
UNG	662	-0.00283	0.06302	-1.25276	0.35149	0.2507	0.24647	-0.2507	6.45035***	0.2507	<.01	<.01	0.39536***
Mauritius													
AIRM	940	-0.00026	0.01611	-0.11507	0.1247	0.24997	0.24997	-0.21173	7.664***	0.24997	<.01	<.01	0.74554***
HAPP	575	0.00034	0.02464	-0.40202	0.37156	0.32362	0.31155	-0.32362	7.76002***	0.32362	<.01	<.01	0.22539***
IREL	845	-0.00003	0.01475	-0.14953	0.07796	0.27364	0.23287	-0.27364	7.95431***	0.27364	<.01	<.01	0.68164***
MCB	978	-0.00033	0.00845	-0.05942	0.05371	0.27633	0.26048	-0.27633	8.64169***	0.27633	<.01	<.01	0.80444***
NMH	967	-0.00022	0.01269	-0.11507	0.12588	0.23686	0.22642	-0.23686	7.3657***	0.23686	<.01	<.01	0.70288***
ROG	697	0.00057	0.00985	-0.06213	0.06454	0.28473	0.26908	-0.28473	7.51701***	0.28473	<.01	<.01	0.74718***
STBK	1033	-0.00029	0.01189	-0.07796	0.08701	0.2918	0.25225	-0.2918	9.37847***	0.2918	<.01	<.01	0.76548***
SUNR	809	-0.00037	0.01092	-0.06575	0.09764	0.26507	0.21824	-0.26507	7.53949***	0.26507	<.01	<.01	0.68525***
UTDB	597	0.00027	0.01004	-0.07303	0.06233	0.29162	0.23769	-0.29162	7.12542***	0.29162	<.01	<.01	0.69052***
Morocco													
ACR	196	0.00392	0.02006	-0.06188	0.05827	0.29362	0.29362	-0.16553	4.11071***	0.29362	<.01	<.01	0.7893***
ATH	352	0.00012	0.02336	-0.09531	0.23513	0.23888	0.23888	-0.22482	4.48182***	0.23888	<.01	<.01	0.68297***
BAL	78	0.00576	0.01416	-0.02128	0.05806	0.2544	0.2544	-0.20647	2.24677***	0.2544	<.01	<.01	0.76835***
BCE	1336	-0.00001	0.01209	-0.13909	0.11511	0.16029	0.16029	-0.14187	5.85868***	0.16029	<.01	<.01	0.78706***
BCI	1122	0.00068	0.01433	-0.06188	0.07593	0.16592	0.16592	-0.15963	5.55758***	0.16592	<.01	<.01	0.88923***
BCM	1258	0.00008	0.01159	-0.08263	0.09406	0.21256	0.21256	-0.18634	7.53918***	0.21256	<.01	<.01	0.76303***
BDE	1088	-0.00064	0.02056	-0.22994	0.14518	0.17504	0.17504	-0.16412	5.77362***	0.17504	<.01	<.01	0.82309***
BER	334	0.0028	0.01925	-0.06291	0.05942	0.18193	0.18193	-0.14492	3.32497***	0.18193	<.01	<.01	0.90883***
BNM	373	0.00161	0.01782	-0.06175	0.12011	0.23238	0.23238	-0.18174	4.48809***	0.23238	<.01	<.01	0.78411***
CDM	893	0.00023	0.01688	-0.09812	0.05896	0.16955	0.16955	-0.14582	5.06668***	0.16955	<.01	<.01	0.88107***
CIH	1186	-0.00096	0.02006	-0.0978	0.05889	0.16471	0.16471	-0.12619	5.67224***	0.16471	<.01	<.01	0.93762***
CLT	540	0.00073	0.01925	-0.06188	0.14105	0.22035	0.22035	-0.219	5.12057***	0.22035	<.01	<.01	0.77166***
CMA	922	0.00056	0.01685	-0.1874	0.17209	0.17824	0.17824	-0.16894	5.41205***	0.17824	<.01	<.01	0.74827***
CRD	1033	-0.00026	0.0211	-0.15391	0.05841	0.16645	0.13847	-0.16645	5.34973***	0.16645	<.01	<.01	0.88985***
CRN	62	0.00143	0.01199	-0.03	0.04282	0.23007	0.23007	-0.22552	1.81158***	0.23007	<.01	<.01	0.81419***
CSR	729	-0.00063	0.01974	-0.07411	0.09456	0.18309	0.18309	-0.17538	4.94348***	0.18309	<.01	<.01	0.87736***
CTM	1171	0.0001	0.01615	-0.06661	0.05842	0.19169	0.17793	-0.19169	6.55978***	0.19169	<.01	<.01	0.86523***
DIS	587	0.00105	0.02019	-0.06306	0.17395	0.22942	0.22942	-0.16771	5.55852***	0.22942	<.01	<.01	0.75004***
EQD	1154	0.00002	0.02266	-0.22935	0.23287	0.15682	0.15682	-0.14501	5.32718***	0.15682	<.01	<.01	0.79742***
FRT	964	-0.00016	0.02327	-0.12029	0.16645	0.16139	0.14566	-0.16139	5.01102***	0.16139	<.01	<.01	0.90731***
GTM	656	-0.00182	0.01717	-0.06454	0.06169	0.1748	0.17123	-0.1748	4.47715***	0.1748	<.01	<.01	0.9066***
HOL	1261	0.0006	0.01574	-0.17693	0.1538	0.15563	0.15563	-0.14717	5.52637***	0.15563	<.01	<.01	0.79062***
LCT	33	0.00211	0.01259	-0.01444	0.05264	0.3832	0.3832	-0.19026	2.20134***	0.3832	<.01	<.01	0.58687***
LES	625	0.00004	0.01663	-0.08201	0.08673	0.17864	0.17864	-0.17151	4.46597***	0.17864	<.01	<.01	0.8517***
LGM	107	0.00018	0.01914	-0.09181	0.05736	0.24822	0.18566	-0.24822	2.5676***	0.24822	<.01	<.01	0.7938***
LGT	600	-0.00088	0.02292	-0.11944	0.08149	0.16798	0.16798	-0.12248	4.11459***	0.16798	<.01	<.01	0.93604***
NEX	636	-0.00021	0.0186	-0.10831	0.05903	0.15593	0.15593	-0.14029	3.9325***	0.15593	<.01	<.01	0.91239***
ONA	1334	0.00035	0.01086	-0.08441	0.07934	0.13944	0.13944	-0.12192	5.09276***	0.13944	<.01	<.01	0.8611***
OUL	411	0.00124	0.02915	-0.16434	0.16331	0.15691	0.15691	-0.12717	3.18111***	0.15691	<.01	<.01	0.90312***
REB	72	0.00139	0.01765	-0.06163	0.05827	0.22036	0.20713	-0.22036	1.8698***	0.22036	<.01	<.01	0.80979***
SBM	935	-0.00049	0.01727	-0.11778	0.126	0.19671	0.19671	-0.17906	6.01487***	0.19671	<.01	<.01	0.80749***
SID	1308	0.00031	0.01644	-0.18232	0.16834	0.12951	0.12951	-0.11054	4.6839***	0.12951	<.01	<.01	0.83427***
SNI	1322	0.00027	0.01229	-0.07465	0.06695	0.13568	0.13568	-0.12107	4.93338***	0.13568	<.01	<.01	0.86658***
SOF	425	0.00222	0.01858	-0.06252	0.07696	0.21458	0.21458	-0.17496	4.42362***	0.21458	<.01	<.01	0.83192***
WFB	1304	0.00009	0.01448	-0.11242	0.11129	0.12543	0.12543	-0.12135	4.52924***	0.12543	<.01	<.01	0.88804***
ZDJ	245	0.00102	0.01746	-0.06213	0.05809	0.19475	0.19475	-0.1692	3.04825***	0.19475	<.01	<.01	0.85365***
Namibia													
AOX	163	-0.00259	0.02162	-0.09844	0.08986	0.15155	0.14365	-0.15155	1.93484***	0.15155	<.01	<.01	0.88012***
API	27	0.00094	0.01224	-0.02228	0.04558	0.3824	0.3824	-0.21158	1.987***	0.3824	<.01	<.01	0.67099***
BLW	327	-0.00126	0.02005	-0.1272	0.05998	0.12161	0.09841	-0.12161	2.19914***	0.12161	<.01	<.01	0.89446***
CIC	231	0.00208	0.05839	-0.40547	0.44183	0.29451	0.29451	-0.26121	4.47614***	0.29451	<.01	<.01	0.52089***
GNB	178	0.00107	0.01935	-0.08847	0.1466	0.19757	0.17044	-0.19757	2.63593***	0.19757	<.01	<.01	0.71222***
KOL	31	0.00336	0.0446	-0.06307	0.12604	0.24945	0.24945	-0.12754	1.38888**	0.24945	<.05	<.01	0.84157***
MRL	327	0.0017	0.0212	-0.08478	0.10536	0.16278	0.16278	-0.11096	2.94351***	0.16278	<.01	<.01	0.87831***
MTF	139	0.00015	0.01156	-0.04282	0.04082	0.19122	0.13816	-0.19122	2.25442***	0.19122	<.01	<.01	0.85721***

Stock	N	Normal Parameters		Minimum	Maximum	Most Extreme Differences			Kolmogorov-Smirnov			Lilliefors p	Shapiro-Wilk W-stat
		Mean	Std. Dev.			Absolute	Positive	Negative	Z-stat	d-stat	p		
NAS	189	-0.00322	0.05546	-0.31845	0.17834	0.22976	0.18052	-0.22976	3.15869***	0.22976	<.01	<.01	0.75977***
NBS	503	0.00164	0.02265	-0.16834	0.16834	0.2326	0.2326	-0.22189	5.21659***	0.2326	<.01	<.01	0.69506***
NCT	67	0.00057	0.01284	-0.05129	0.05609	0.31345	0.30887	-0.31345	2.56569***	0.31345	<.01	<.01	0.64782***
NMC	188	0.00052	0.04305	-0.25541	0.18865	0.28778	0.28778	-0.21932	3.94588***	0.28778	<.01	<.01	0.68891***
NMF	126	0.0018	0.04377	-0.22314	0.29389	0.27934	0.27934	-0.24615	3.13562***	0.27934	<.01	<.01	0.52838***
PNB	89	-0.00538	0.03752	-0.18232	0.13516	0.28603	0.2794	-0.28603	2.69838***	0.28603	<.01	<.01	0.58187***
SRM	73	0.00483	0.02393	-0.01606	0.1431	0.36655	0.36655	-0.26976	3.13178***	0.36655	<.01	<.01	0.37139***
STB	425	0.00123	0.02156	-0.09894	0.13787	0.14687	0.14687	-0.11487	3.02773***	0.14687	<.01	<.01	0.87244***
							Tunisia						
ALIQ	192	0.0007	0.01692	-0.11969	0.02956	0.24265	0.16188	-0.24265	3.36233***	0.24265	<.01	<.01	0.73862***
ALK	712	-0.00011	0.01213	-0.09481	0.04403	0.21404	0.19798	-0.21404	5.71142***	0.21404	<.01	<.01	0.81337***
AB	854	0.00051	0.01193	-0.04263	0.03898	0.22782	0.22782	-0.18148	6.65768***	0.22782	<.01	<.01	0.87879***
ALSE	688	0.0011	0.01354	-0.05879	0.0426	0.17589	0.17589	-0.14528	4.61358***	0.17589	<.01	<.01	0.90278***
AMS	765	0.00118	0.01421	-0.06543	0.04546	0.21066	0.2023	-0.21066	5.82668***	0.21066	<.01	<.01	0.88092***
ASTR	107	0.00409	0.01664	-0.01506	0.15355	0.33174	0.33174	-0.29352	3.43154***	0.33174	<.01	<.01	0.35381***
ATB	808	-0.00025	0.01182	-0.07702	0.05629	0.25061	0.25061	-0.21752	7.12379***	0.25061	<.01	<.01	0.81214***
ATL	1110	0.00021	0.01388	-0.10035	0.05015	0.19805	0.19805	-0.14464	6.59833***	0.19805	<.01	<.01	0.88198***
BH	1174	-0.00027	0.01242	-0.11681	0.07951	0.16761	0.16761	-0.11779	5.74299***	0.16761	<.01	<.01	0.89487***
BIAT	1186	-0.0001	0.01073	-0.08149	0.12396	0.17734	0.17734	-0.17228	6.10713***	0.17734	<.01	<.01	0.79927***
BNA	1043	-0.00001	0.0105	-0.06608	0.04419	0.21196	0.21196	-0.15268	6.84535***	0.21196	<.01	<.01	0.86911***
BS	1171	0.00008	0.0118	-0.08085	0.04343	0.21322	0.21322	-0.18131	7.29639***	0.21322	<.01	<.01	0.85352***
BT	1139	0.00013	0.00815	-0.1562	0.1179	0.38277	0.38277	-0.36842	12.91811***	0.38277	<.01	<.01	0.31068***
BTA	1172	-0.00012	0.00829	-0.09483	0.02931	0.22067	0.20736	-0.22067	7.55462***	0.22067	<.01	<.01	0.7016***
CIL	983	0.00016	0.01408	-0.10629	0.03739	0.17354	0.17354	-0.15584	5.44093***	0.17354	<.01	<.01	0.89993***
ECF	340	0.00004	0.0086	-0.04162	0.02956	0.30034	0.21885	-0.30034	5.53809***	0.30034	<.01	<.01	0.72611***
LCT	243	0.00113	0.01211	-0.06018	0.02948	0.31819	0.31819	-0.23055	4.96008***	0.31819	<.01	<.01	0.74608***
MPX	976	-0.00003	0.00911	-0.05884	0.05874	0.27754	0.27754	-0.27019	8.67076***	0.27754	<.01	<.01	0.70897***
PB	160	-0.00033	0.0106	-0.03041	0.03137	0.22167	0.2204	-0.22167	2.80389***	0.22167	<.01	<.01	0.84244***
PBA	426	-0.0005	0.00983	-0.10035	0.03227	0.29728	0.24647	-0.29728	6.13569***	0.29728	<.01	<.01	0.65353***
PTUN	269	0.00231	0.01127	-0.03559	0.03347	0.21797	0.21797	-0.20584	3.57498***	0.21797	<.01	<.01	0.83209***
SFBT	1210	0.00102	0.01536	-0.12461	0.05809	0.11953	0.11953	-0.08123	4.15796***	0.11953	<.01	<.01	0.93712***
SIMP	314	0.00076	0.01217	-0.04948	0.0438	0.2304	0.2304	-0.20071	4.08268***	0.2304	<.01	<.01	0.84528***
SITX	537	0.0008	0.0148	-0.0678	0.04374	0.21614	0.21614	-0.16275	5.00877***	0.21614	<.01	<.01	0.87975***
SOFI	430	0.00237	0.01722	-0.05988	0.08754	0.19425	0.19425	-0.14795	4.02795***	0.19425	<.01	<.01	0.91479***
SPDT	1107	0.0002	0.01394	-0.06511	0.04452	0.2069	0.2069	-0.1436	6.8839***	0.2069	<.01	<.01	0.90864***
STAR	454	0.00067	0.01282	-0.04563	0.06062	0.22603	0.22603	-0.15973	4.81599***	0.22603	<.01	<.01	0.86593***
STB	1226	-0.00027	0.01109	-0.08062	0.04508	0.18865	0.18865	-0.1142	6.60529***	0.18865	<.01	<.01	0.90343***
STIL	289	0.00116	0.01934	-0.05808	0.07118	0.1571	0.1571	-0.10242	2.67069***	0.1571	<.01	<.01	0.9589***
TVST	891	0.00014	0.01049	-0.05085	0.0431	0.26064	0.26064	-0.23992	7.77991***	0.26064	<.01	<.01	0.78573***
TAIR	1218	-0.00113	0.01554	-0.13178	0.05815	0.12872	0.12872	-0.0868	4.49237***	0.12872	<.01	<.01	0.93418***
TLAI	108	0.00086	0.01335	-0.04667	0.05578	0.21594	0.21594	-0.20923	2.24407***	0.21594	<.01	<.01	0.82993***
TLSE	997	0.00007	0.0127	-0.10277	0.06024	0.19415	0.18265	-0.19415	6.13049***	0.19415	<.01	<.01	0.85912***
UBCI	1001	-0.00026	0.01145	-0.04607	0.05444	0.2042	0.2042	-0.18954	6.46063***	0.2042	<.01	<.01	0.86324***
UIB	1152	0.00005	0.01123	-0.0661	0.04414	0.22414	0.22414	-0.18645	7.60759***	0.22414	<.01	<.01	0.87254***
							Zimbabwe						
APEX	504	0.0044	0.04721	-0.28768	0.40547	0.20376	0.20376	-0.19306	4.57444***	0.20376	<.01	<.01	0.71075***
ARIS	687	0.00231	0.02916	-0.22314	0.15028	0.22091	0.19249	-0.22091	5.79008***	0.22091	<.01	<.01	0.84535***
ASHA	285	0.00783	0.05185	-0.40547	0.28768	0.23646	0.23021	-0.23646	3.99185***	0.23646	<.01	<.01	0.65455***
BARC	1293	0.00238	0.03235	-0.38441	0.22314	0.24642	0.18282	-0.24642	8.86072***	0.24642	<.01	<.01	0.73124***
BICC	361	0.0029	0.03395	-0.28768	0.15415	0.21662	0.15411	-0.21662	4.11586***	0.21662	<.01	<.01	0.77439***
BIND	761	0.00347	0.05119	-0.50078	0.38441	0.21411	0.19851	-0.21411	5.90644***	0.21411	<.01	<.01	0.71449***
BORD	236	0.00012	0.03144	-0.16824	0.13353	0.19336	0.14988	-0.19336	2.97042***	0.19336	<.01	<.01	0.78785***
CAPS	758	0.00431	0.04901	-0.66648	0.25131	0.18368	0.18368	-0.18133	5.05695***	0.18368	<.01	<.01	0.70172***
CHEM	173	0.01009	0.06702	-0.13228	0.69315	0.27999	0.27999	-0.21948	3.68272***	0.27999	<.01	<.01	0.45692***
CIRC	304	0.0003	0.02821	-0.11192	0.13353	0.18654	0.15228	-0.18654	3.25241***	0.18654	<.01	<.01	0.87522***
CLAN	690	0.00215	0.05227	-0.26236	0.33647	0.23577	0.22944	-0.23577	6.19323***	0.23577	<.01	<.01	0.84587***
COLC	940	0.00154	0.04078	-0.28768	0.19783	0.21362	0.19276	-0.21362	6.54957***	0.21362	<.01	<.01	0.81782***
DELT	1263	0.00172	0.0299	-0.17869	0.22314	0.21739	0.21254	-0.21739	7.72566***	0.21739	<.01	<.01	0.77491***
DWHI	729	0.00162	0.09178	-0.40547	1.04145	0.2217	0.2217	-0.20354	5.98596***	0.2217	<.01	<.01	0.81101***
EDGA	885	0.00251	0.03912	-0.30228	0.20067	0.22128	0.21827	-0.22128	6.58276***	0.22128	<.01	<.01	0.82895***
FALC	235	0.00602	0.05127	-0.25773	0.40547	0.26162	0.26162	-0.22775	4.0105***	0.26162	<.01	<.01	0.63156***
FALG	719	0.00072	0.08385	-1.09861	0.44183	0.23234	0.22524	-0.23234	6.22994***	0.23234	<.01	<.01	0.72451***
FINH	570	0.00366	0.0557	-0.40547	0.29439	0.20613	0.16755	-0.20613	4.92135***	0.20613	<.01	<.01	0.72999***
GULL	455	0.0087	0.04641	-0.26826	0.28768	0.1897	0.1897	-0.18173	4.04649***	0.1897	<.01	<.01	0.80653***
HIPP	725	0.00209	0.02859	-0.14384	0.33647	0.23093	0.20631	-0.23093	6.21793***	0.23093	<.01	<.01	0.71686***
HSLY	81	0.00088	0.05742	-0.28768	0.22314	0.28526	0.26412	-0.28526	2.56738***	0.28526	<.01	<.01	0.65139***
HUNY	847	0.00213	0.03922	-0.17834	0.31015	0.22763	0.22763	-0.21157	6.62474***	0.22763	<.01	<.01	0.81651***
KING	1161	0.00288	0.05488	-0.54232	0.54232	0.19793	0.19793	-0.19742	6.74427***	0.19793	<.01	<.01	0.74706***
MEIK	957	0.00202	0.03008	-0.18232	0.30637	0.20573	0.20179	-0.20573	6.36436***	0.20573	<.01	<.01	0.7504***
NATF	408	0.00547	0.04253	-0.27981	0.22314	0.21602	0.18114	-0.21602	4.3633***	0.21602	<.01	<.01	0.76312***
NTS	299	0.0072	0.04594	-0.22314	0.33647	0.1954	0.1954	-0.1879	3.37876***	0.1954	<.01	<.01	0.73711***
PGI	879	0.00515	0.06452	-0.36772	0.43825	0.19164	0.19164	-0.1872	5.68185***	0.19164	<.01	<.01	0.81585***

Stock	N	Normal Parameters		Minimum	Maximum	Most Extreme Differences			Kolmogorov-Smirnov			Lilliefors p	Shapiro-Wilk W-stat
		Mean	Std. Dev.			Absolute	Positive	Negative	Z-stat	d-stat	p		
RADA	519	0.00154	0.04319	-0.28768	0.39499	0.19872	0.15774	-0.19872	4.52714***	0.19872	<.01	<.01	0.77471***
RIO	478	0.00088	0.03677	-0.23361	0.19531	0.23312	0.19366	-0.23312	5.09674***	0.23312	<.01	<.01	0.74171***
SEED	1019	0.00268	0.04065	-0.22314	0.51083	0.20778	0.19458	-0.20778	6.6327***	0.20778	<.01	<.01	0.7648***
TA	947	0.00351	0.05258	-0.32542	0.27029	0.23049	0.21407	-0.23049	7.09307***	0.23049	<.01	<.01	0.81345***
TANG	575	0.0055	0.02795	-0.10536	0.28418	0.20455	0.18502	-0.20455	4.90494***	0.20455	<.01	<.01	0.76569***
TEDC	805	0.00167	0.04189	-0.40547	0.2442	0.24312	0.22893	-0.24312	6.89785***	0.24312	<.01	<.01	0.75901***
TRUW	613	0.00565	0.05805	-0.69315	0.30603	0.19131	0.19131	-0.18553	4.73654***	0.19131	<.01	<.01	0.69003***
TSL	660	0.00236	0.03735	-0.20764	0.28768	0.18733	0.18733	-0.16722	4.81249***	0.18733	<.01	<.01	0.81171***
WCOL	924	0.00107	0.05407	-0.63599	0.35667	0.23775	0.22329	-0.23775	7.22694***	0.23775	<.01	<.01	0.63418***
ZPAP	997	-0.00032	0.06589	-0.8141	0.33647	0.2321	0.21725	-0.2321	7.32862***	0.2321	<.01	<.01	0.78598***
ZPLO	257	0.00613	0.05277	-0.40547	0.32542	0.21958	0.18757	-0.21958	3.52015***	0.21958	<.01	<.01	0.69438***
ZSUN	947	0.00041	0.0434	-0.40547	0.21357	0.24704	0.20069	-0.24704	7.60212***	0.24704	<.01	<.01	0.7765***

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level
Source: Chipo Mlambo (2004), University of Stellenbosch Business School

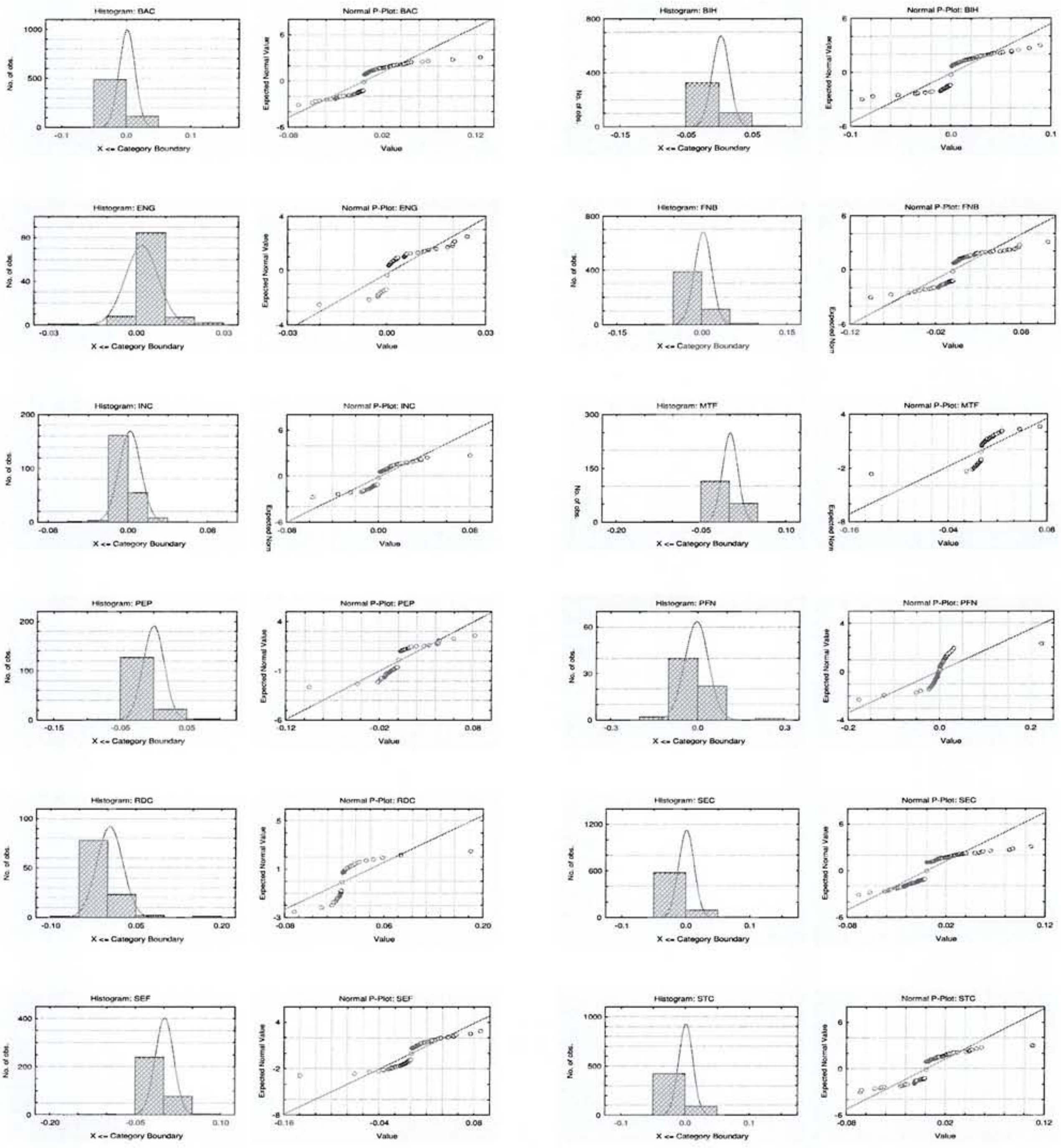
APPENDIX E

GRAPHICAL PRESENTATION OF DATA NORMALITY

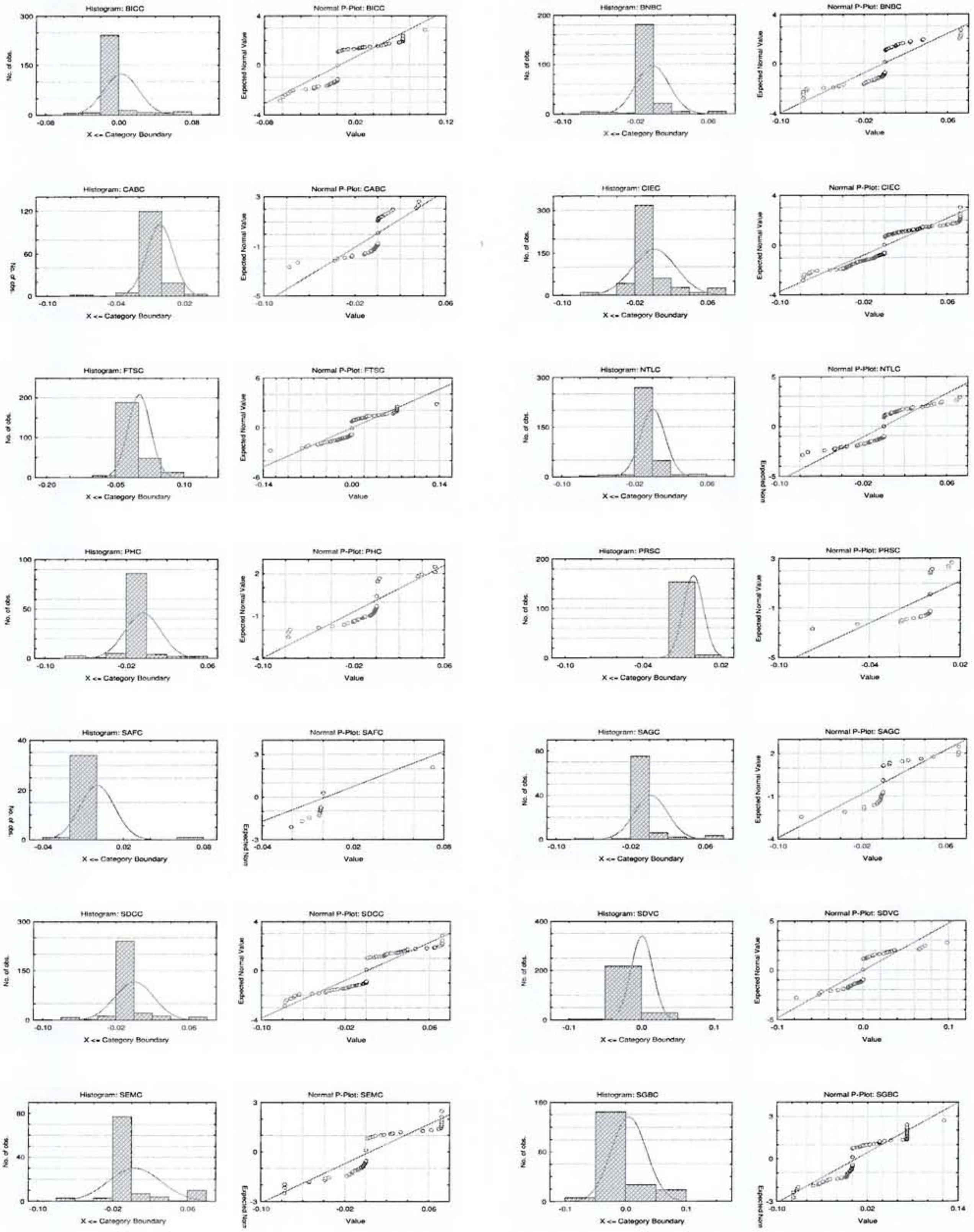
----------HISTOGRAMS & NORMAL PROBABILITY PLOTS----------

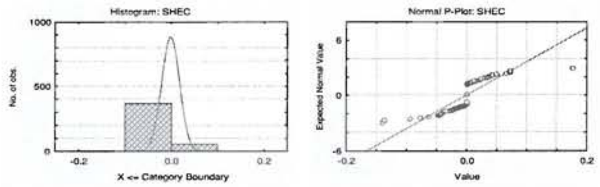
Appendix E: Histograms and normal probability plots

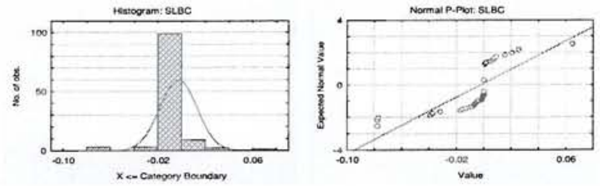
Botswana

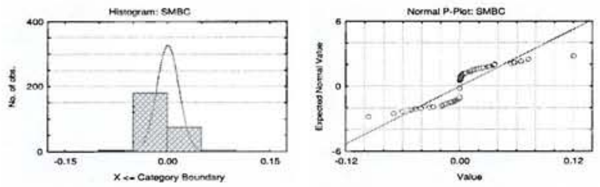


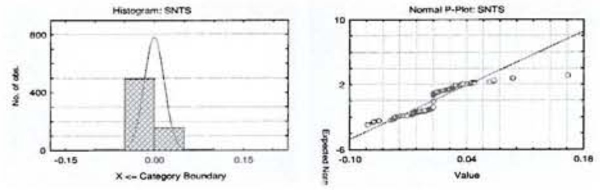
BRVM

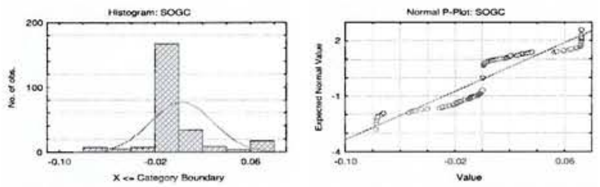

Histogram: BICC
Normal P-Plot: BICC
Histogram: BNBC
Normal P-Plot: BNBC
Histogram: CABC
Normal P-Plot: CABC
Histogram: CIEC
Normal P-Plot: CIEC
Histogram: FTSC
Normal P-Plot: FTSC
Histogram: NTLC
Normal P-Plot: NTLC
Histogram: PHC
Normal P-Plot: PHC
Histogram: PRSC
Normal P-Plot: PRSC
Histogram: SAFC
Normal P-Plot: SAFC
Histogram: SAGC
Normal P-Plot: SAGC
Histogram: SDCC
Normal P-Plot: SDCC
Histogram: SDVC
Normal P-Plot: SDVC
Histogram: SEMC
Normal P-Plot: SEMC
Histogram: SGBC
Normal P-Plot: SGBC
No. of obs.
Expected Normal Value
X <= Category Boundary
Value

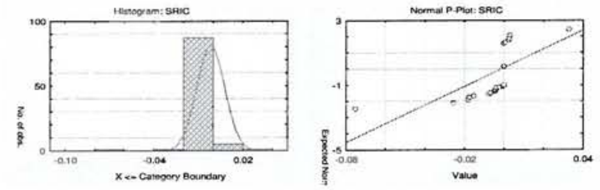

Histogram: SHEC
No. of obs.
X <= Category Boundary
Normal P-Plot: SHEC
Expected Normal Value
Value

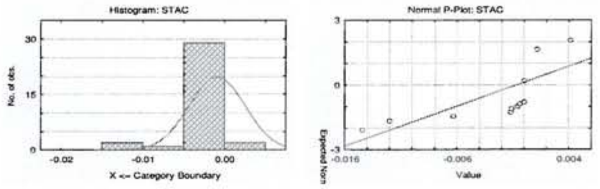

Histogram: SLBC
No. of obs.
X <= Category Boundary
Normal P-Plot: SLBC
Expected Normal Value
Value

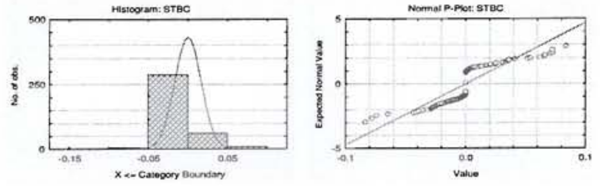

Histogram: SMBC
No. of obs.
X <= Category Boundary
Normal P-Plot: SMBC
Expected Normal Value
Value

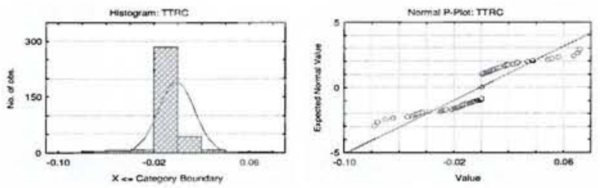

Histogram: SNTS
No. of obs.
X <= Category Boundary
Normal P-Plot: SNTS
Value

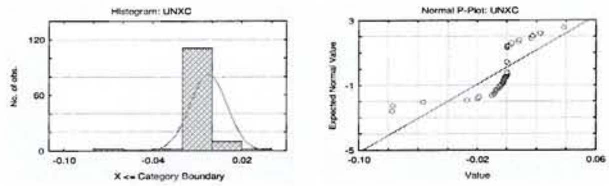

Histogram: SOGC
No. of obs.
X <= Category Boundary
Normal P-Plot: SOGC
Expected Normal Value
Value


Histogram: SRIC
X <= Category Boundary
Normal P-Plot: SRIC
Value

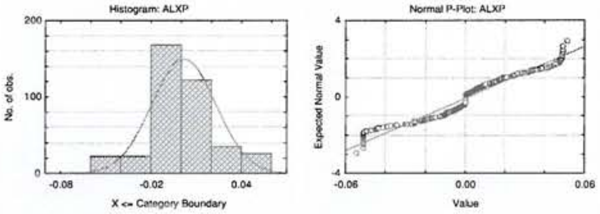

Histogram: STAC
No. of obs.
X <= Category Boundary
Normal P-Plot: STAC
Value

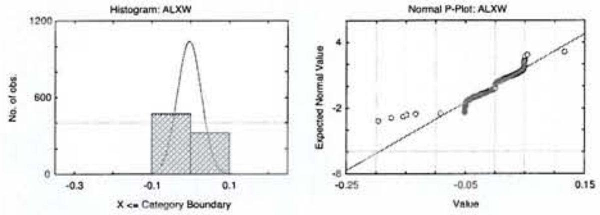

Histogram: STBC
No. of obs.
X <= Category Boundary
Normal P-Plot: STBC
Expected Normal Value
Value

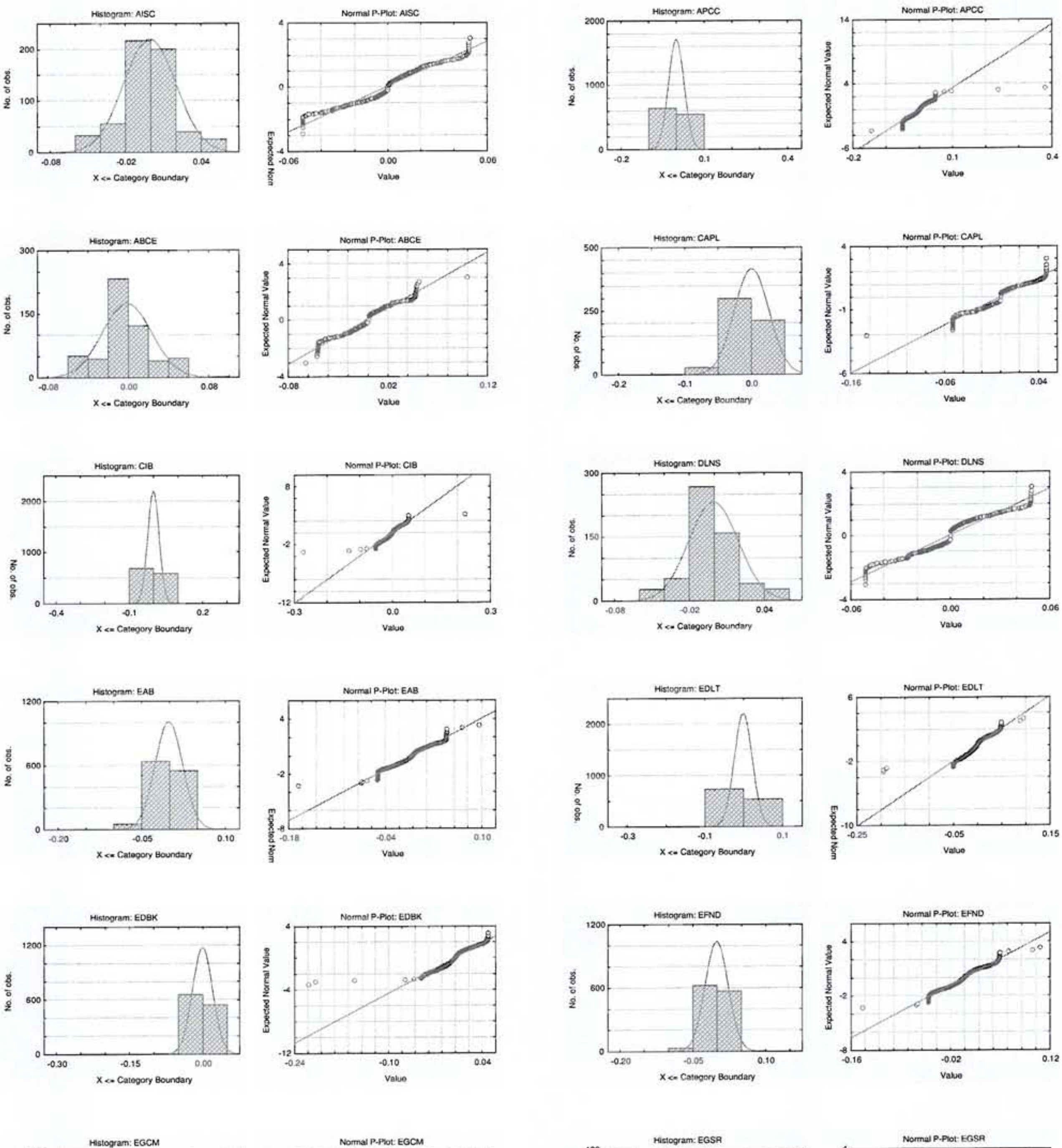

Histogram: TTRC
No. of obs.
X <= Category Boundary
Normal P-Plot: TTRC
Expected Normal Value
Value

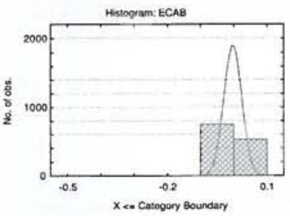
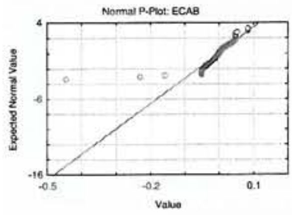
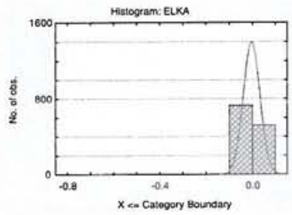
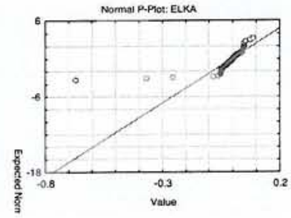
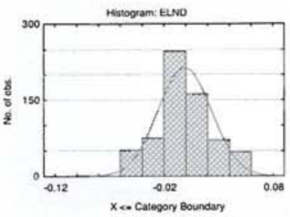
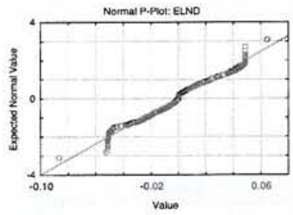
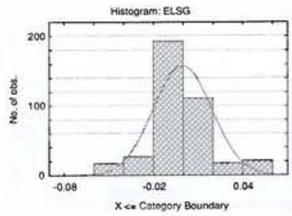
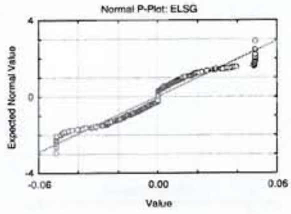
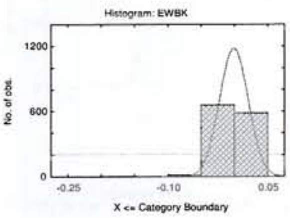
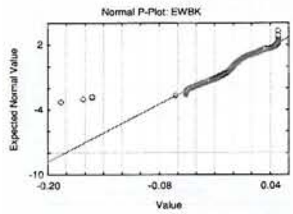
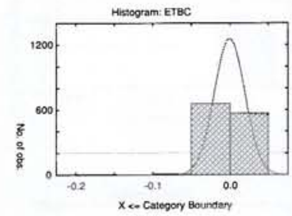
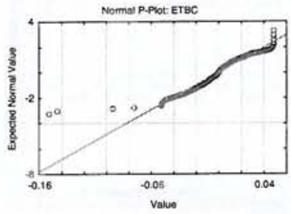
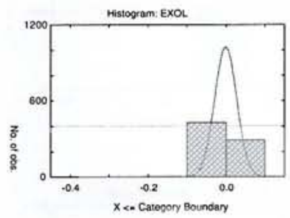
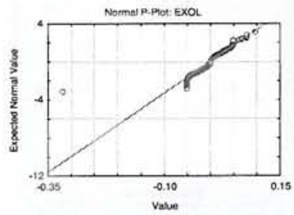
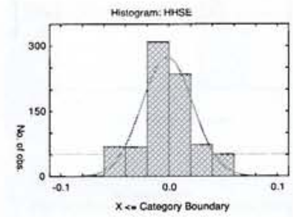
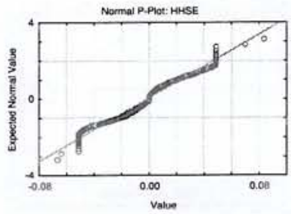
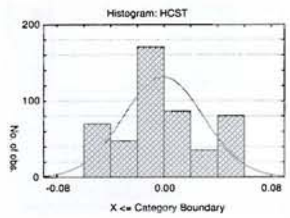
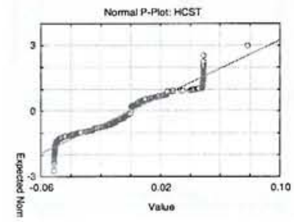
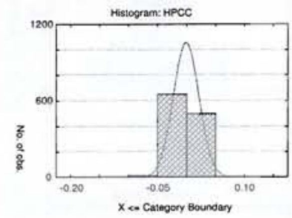
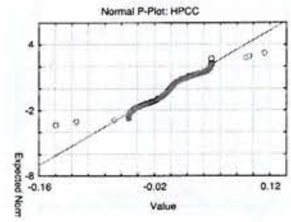
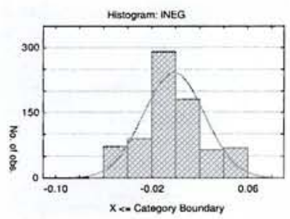
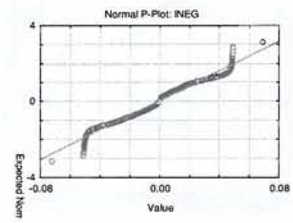
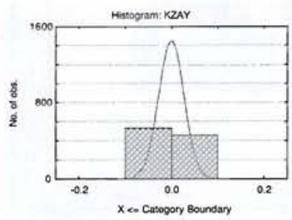
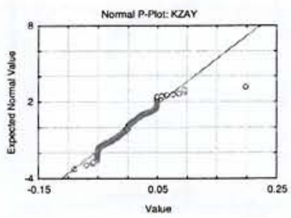

Histogram: UNXC
No. of obs.
X <= Category Boundary
Normal P-Plot: UNXC
Expected Normal Value
Value

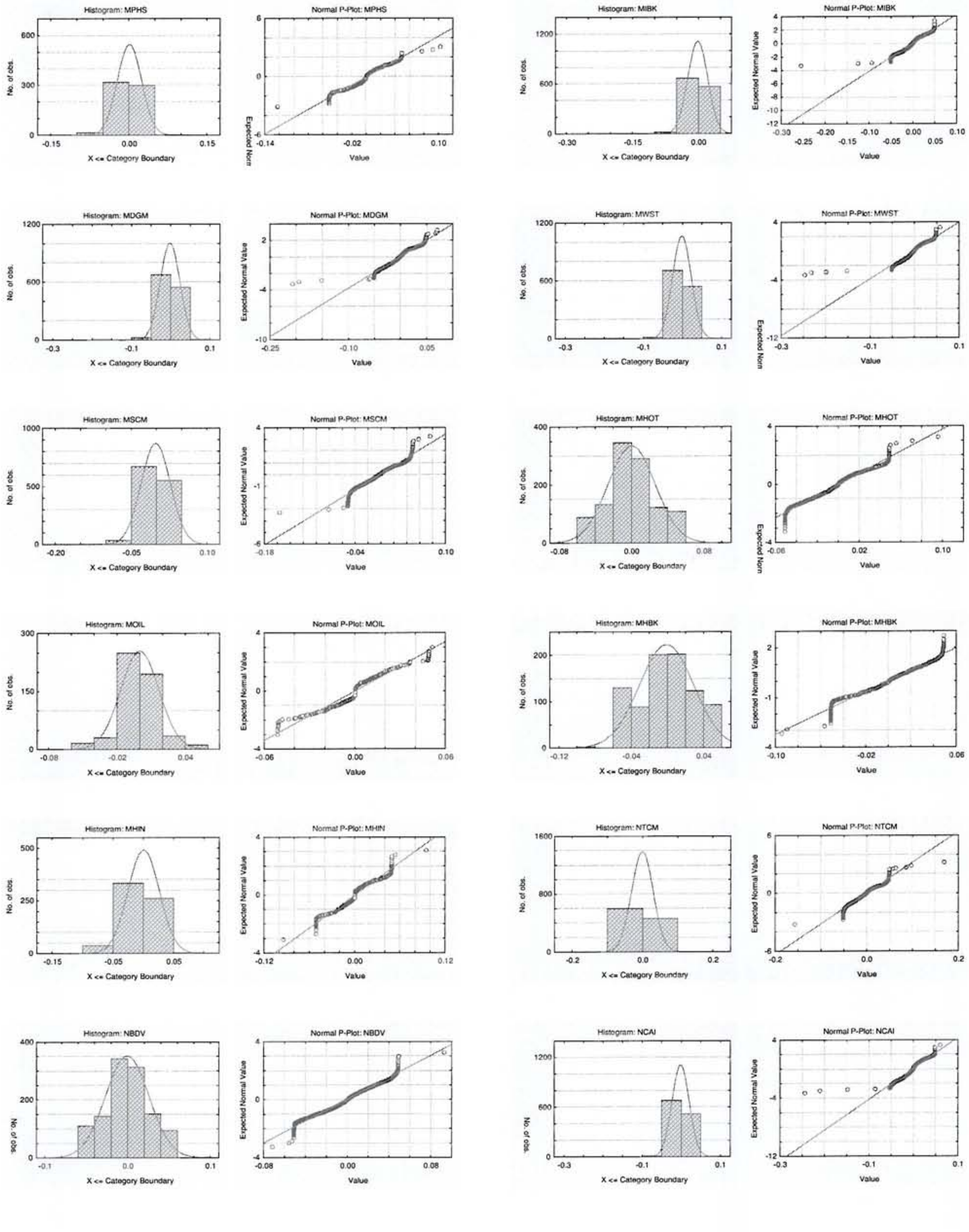
Egypt

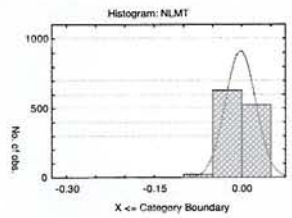

Histogram: ALXP
No. of obs.
X <= Category Boundary
Normal P-Plot: ALXP
Expected Normal Value
Value

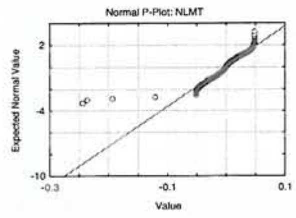

Histogram: ALXW
No. of obs.
X <= Category Boundary
Normal P-Plot: ALXW
Expected Normal Value
Value

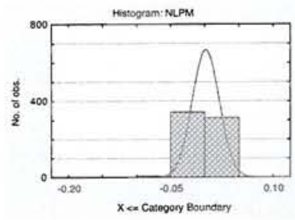

Histogram: AISC
No. of obs.
X <= Category Boundary
Normal P-Plot: AISC
Expected Norm
Value
Histogram: APCC
No. of obs.
X <= Category Boundary
Normal P-Plot: APCC
Expected Normal Value
Value
Histogram: ABCE
No. of obs.
X <= Category Boundary
Normal P-Plot: ABCE
Expected Normal Value
Value
Histogram: CAPL
No. of obs.
X <= Category Boundary
Normal P-Plot: CAPL
Expected Normal Value
Value
Histogram: CIB
No. of obs.
X <= Category Boundary
Normal P-Plot: CIB
Expected Normal Value
Value
Histogram: DLNS
No. of obs.
X <= Category Boundary
Normal P-Plot: DLNS
Expected Normal Value
Value
Histogram: EAB
No. of obs.
X <= Category Boundary
Normal P-Plot: EAB
Expected Norm
Value
Histogram: EDLT
No. of obs.
X <= Category Boundary
Normal P-Plot: EDLT
Expected Norm
Value
Histogram: EDBK
No. of obs.
X <= Category Boundary
Normal P-Plot: EDBK
Expected Normal Value
Value
Histogram: EFND
No. of obs.
X <= Category Boundary
Normal P-Plot: EFND
Expected Normal Value
Value
Histogram: EGCM
No. of obs.
X <= Category Boundary
Normal P-Plot: EGCM
Expected Normal Value
Value
Histogram: EGSR
No. of obs.
X <= Category Boundary
Normal P-Plot: EGSR
Expected Normal Value
Value

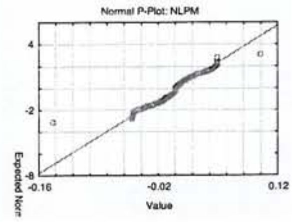

Histogram: ECAB
No. of obs.
X <= Category Boundary

Normal P-Plot: ECAB
Expected Normal Value
Value

Histogram: ELKA
No. of obs.
X <= Category Boundary

Normal P-Plot: ELKA
Expected Norm
Value

Histogram: ELND
No. of obs.
X <= Category Boundary

Normal P-Plot: ELND
Expected Normal Value
Value

Histogram: ELSG
No. of obs.
X <= Category Boundary

Normal P-Plot: ELSG
Expected Normal Value
Value

Histogram: EWBK
No. of obs.
X <= Category Boundary

Normal P-Plot: EWBK
Expected Normal Value
Value

Histogram: ETBC
No. of obs.
X <= Category Boundary

Normal P-Plot: ETBC
Expected Normal Value
Value

Histogram: EXOL
No. of obs.
X <= Category Boundary

Normal P-Plot: EXOL
Expected Normal Value
Value

Histogram: HHSE
No. of obs.
X <= Category Boundary

Normal P-Plot: HHSE
Expected Normal Value
Value

Histogram: HCST
No. of obs.
X <= Category Boundary

Normal P-Plot: HCST
Expected Norm
Value

Histogram: HPCC
No. of obs.
X <= Category Boundary

Normal P-Plot: HPCC
Expected Norm
Value

Histogram: INEG
No. of obs.
X <= Category Boundary

Normal P-Plot: INEG
Expected Norm
Value

Histogram: KZAY
No. of obs.
X <= Category Boundary

Normal P-Plot: KZAY
Expected Normal Value
Value

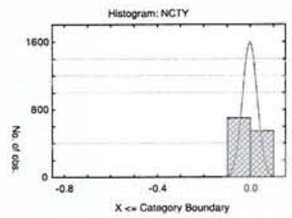

Histogram: MPHS
Normal P-Plot: MPHS
Histogram: MIBK
Normal P-Plot: MIBK
Histogram: MDGM
Normal P-Plot: MDGM
Histogram: MWST
Normal P-Plot: MWST
Histogram: MSCM
Normal P-Plot: MSCM
Histogram: MHOT
Normal P-Plot: MHOT
Histogram: MOIL
Normal P-Plot: MOIL
Histogram: MHBK
Normal P-Plot: MHBK
Histogram: MHIN
Normal P-Plot: MHIN
Histogram: NTCM
Normal P-Plot: NTCM
Histogram: NBDV
Normal P-Plot: NBDV
Histogram: NCAI
Normal P-Plot: NCAI
No. of obs.
X <= Category Boundary
Expected Normal Value
Value

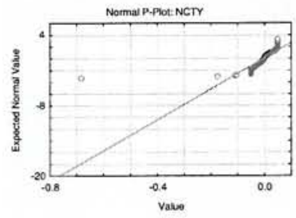

Histogram: NLMT
No. of obs.
X <= Category Boundary

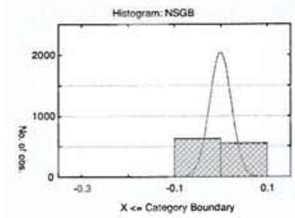

Normal P-Plot: NLMT
Expected Normal Value
Value

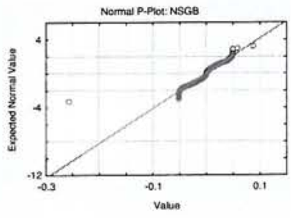

Histogram: NLPM
No. of obs.
X <= Category Boundary

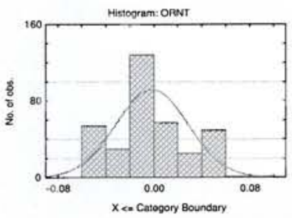

Normal P-Plot: NLPM
Value

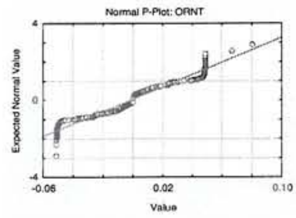

Histogram: NCTY
No. of obs.
X <= Category Boundary


Normal P-Plot: NCTY
Expected Normal Value
Value


Histogram: NSGB
No. of obs.
X <= Category Boundary


Normal P-Plot: NSGB
Expected Normal Value
Value


Histogram: ORNT
No. of obs.
X <= Category Boundary


Normal P-Plot: ORNT
Expected Normal Value
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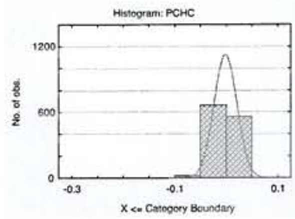
Histogram: PCHC
No. of obs.
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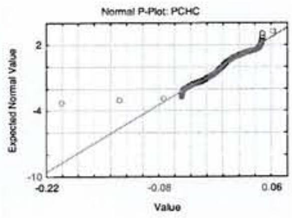
Normal P-Plot: PCHC
Expected Normal Value
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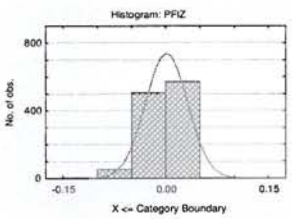
Histogram: PFIZ
No. of obs.
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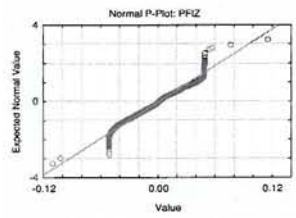
Normal P-Plot: PFIZ
Expected Normal Value
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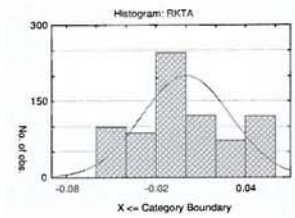
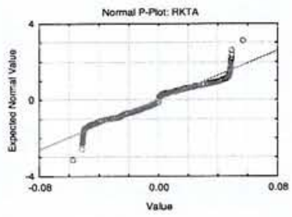
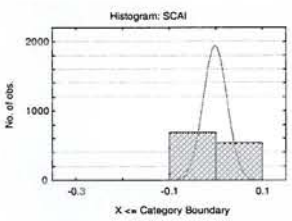
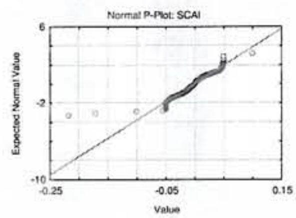
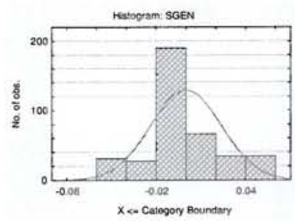
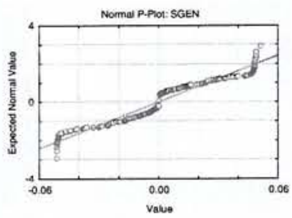

Histogram: RKTA
No. of obs.
X <= Category Boundary

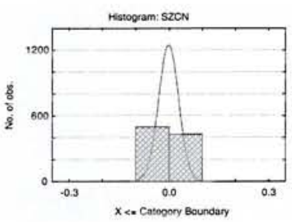

Normal P-Plot: RKTA
Expected Normal Value
Value

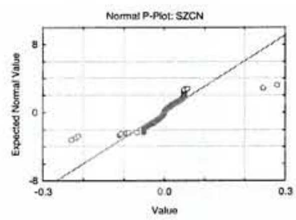

Histogram: SCAI
No. of obs.
X <= Category Boundary

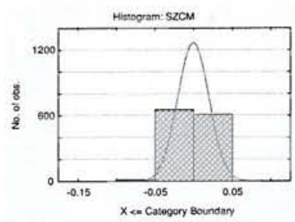

Normal P-Plot: SCAI
Expected Normal Value
Value

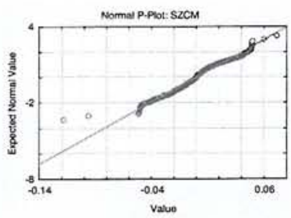

Histogram: SGEN
No. of obs.
X <= Category Boundary


Normal P-Plot: SGEN
Expected Normal Value
Value


Histogram: SZCN
No. of obs.
X <= Category Boundary


Normal P-Plot: SZCN
Expected Normal Value
Value


Histogram: SZCM
No. of obs.
X <= Category Boundary


Normal P-Plot: SZCM
Expected Normal Value
Value